Received: 10 February 2023 | Accepted: 6 January 2024

DOI: 10.1111/1467-8489.12555

The Australian Journal of Agricultural and Resource Economics AARES

ORIGINAL ARTICLE

An integrated assessment model of the impacts of agricultural intensification: Trade-offs between economic benefits and water quality under uncertainty

Augusto Souto[1] | **Miguel Carriquiry**[2] | **Francisco Rosas**[3,4]

[1]Department of Economics, Arizona State University, Tempe, Arizona, USA

[2]Department of Economics, Universidad de la Republica, Montevideo, Uruguay

[3]Department of Economics, Universidad ORT Uruguay, Montevideo, Uruguay

[4]Centro de Investigaciones Economicas (CINVE), Montevideo, Uruguay

Correspondence
Francisco Rosas, Department of Economics, Universidad ORT Uruguay, Montevideo, Uruguay.
Email: rosas@ort.edu.uy

Funding information
Agencia Nacional de Investigación e Innovación (ANII), Uruguay (Fondo Sectorial Innovagro, FSA PI 2018 1 148628)

Abstract

We integrate a model that simulates biophysical processes in soils and water with spatial and temporal heterogeneity at the basin scale with an economic model of decisions under uncertainty, to simultaneously evaluate the economic and environmental effects of farming practices and land uses that characterise agricultural intensification. The introduction of uncertainty allows the evaluation of economic impacts both due to changes in average profits and in their volatility. Through our model integration, we endogenously tackle the trade-offs between economic benefits and environmental outcomes, in terms of nutrient levels in water. Results show that a sizable increase in economic benefits from supplemental irrigation comes from lower risk premiums. Medium-to-high increments of fertiliser rates in irrigated crops are dominated in terms of economic benefits by low fertiliser rate increments. We find that water quality deteriorates with intensive farming practices. However, the magnitude of the trade-offs between economic benefits and water quality is mixed and depends on the nutrient and level of risk aversion considered. The ability of our model to quantify and document the mentioned effects is a relevant input to inform the decision-making process of agricultural and environmental authorities, often characterised by competing and opposing objectives.

KEYWORDS

expected utility, fertiliser, integrated assessment models, land use, supplemented irrigation, SWAT, water quality

JEL CLASSIFICATION

Q15, Q25, Q53, Q55, C63, D81

1 | INTRODUCTION

Increasing global demand for food, fibre and fuels is forcing an accelerated expansion of agricultural output, placing producers and their use of natural resources at centre stage. The growing demand implies enhanced pressure over resources, entailing global consequences that can be traced all the way to regional and local scales. While in certain areas output expansion is the result of increases in the land brought into production (the extensive margin), with limited amounts of land available, the history of the last century has shown that most of the output growth is obtained through the intensification of land already in use (intensive margin), mostly in areas where agriculture is already developed (FAO, 2021; Hertel et al., 2013). This imposes accelerating environmental pressures, in particular, on water quantity and quality (Pretty, 2018). The identification and analysis of sustainable intensification practices are urgently needed, mainly those that balance potentially competing goals such as increasing economic benefits, reducing risk in the face of enhanced rainfall variability due to climate change and preventing water quality impairment. This is the focus of the current paper. We argue that improved integrated assessment models are needed (Khanna et al., 2018; Kling et al., 2017), and contribute with the development of a new model to aid the analysis of the above-mentioned balances in the context of a developing country.

At the local scale, agriculture faces high competition for water from other sectors, such as industry and energy sectors, as well as from the municipal demand (Burek et al., 2016; IEA, 2016). Moreover, water availability and scarcity are time- and space-dependent adding other dimensions to this issue. Averages tend to mask seasonal and intra-annual fluctuations (Mekonnen & Hoekstra, 2016), and the spatial variability of rainfall and water flows within a basin. Water quality impacts are driven not only by farming practices, including those that characterise the development of agriculture along the intensive margin, but also by the municipal and industrial wastewater releases into water bodies. The existence of multiple pollutants from multiple sources, their high spatial and temporal variability, transaction costs and limited political acceptability of regulatory measures impose further challenges for controlling the degradation of water resources (OECD, 2017).

Our study seeks to inform the regulator's decision-making and policy design and implementation to adequately manage water resources in the context of increasing intensification of agricultural production. We develop an integrated model to address these types of problems. The calibration of a biophysical model at the basin scale tackles the issue of local effects, and its spatial structure allows us to assess problems related to diffuse pollution and the pollution from point sources. The fact that the biophysical model runs at daily or monthly time steps incorporates the seasonality and intra-annual fluctuations of the variables driving these problems. The integration with an economic model of decisions under uncertainty captures the impacts of various land uses and farm practices, allowing us to simultaneously analyse the production, economic and environmental effects of the activities carried out within the basin. Unlike typical analyses focussing only on expected returns, our model can also evaluate the contribution to economic benefits arising from the reduction in volatility of returns. Furthermore, we document the trade-offs between economic benefits and water quality through a set of indicators computed with variables that are endogenously determined.

The sustainable availability of water in quantity and quality interacts in complex ways with economic decisions made by economic agents. It both affects and is affected by their choices. These decisions affect the functioning of ecosystems and ecosystem services, and the latter affect the options available to individuals. Analysing these interactions requires a combination of modelling frameworks that simultaneously consider economic and biophysical elements. The assessment of these phenomena has been typically carried out independently through different types of models, which may be roughly grouped into economic models on the one hand, and biophysical models on the other (Kling et al., 2017; Plantinga, 2015). Economic models can assess changes in land use and practices when other (endogenous) economic variables change, but taking biophysical variables as given. On the other hand, biophysical models assess changes in (endogenous) biophysical variables by considering the economic factors that drive land use as exogenous.

More recently, however, under the recognition of the necessity of capturing the interactions and feedback of the different components of the socioecological systems, there has been a strong interest and progress towards developing and using integrated assessment models (IAMs). In contrast to classic economic analysis, this approach could account for omitted links between human and biological systems, allowing for a more comprehensive analysis of the nexus between natural resources and production (Khanna et al., 2018). According to Keiser and Muller (2017), using IAMs to analyse water conservation policies and the benefits of water quality improvements has became widespread in the present century. In addition, Miao and Khanna (2020) highlight these models' usefulness in analysing the impacts of new technologies on agriculture, such as precision farming, gene editing, second-generation biofuels or agrivoltaics. Nonetheless, Dai et al. (2018) note that the analysts must be aware of the scope of different studies using an IAM approach. While most of them present new methodologies to assess the relationship between production and natural resources, studies analysing the technical and political feasibility of implementing the proposed solutions are also needed.

In the IAM literature, the relationship of agricultural intensification practices with economic and environmental outcomes can be divided into two types of approaches according to the number of solutions analysed. The first type explores a large set of agricultural practices to find the optimal combination within the context of a computationally intensive problem. It includes the work by Rabotyagov et al. (2010, 2014) and Pastori et al. (2017), who applied evolutionary algorithm methods to find Pareto-efficient solutions. The second type consists of analysing a limited set of scenarios that are compared against a baseline (Corona et al., 2020; Griffin et al., 2020; Lee et al., 2012; Liu et al., 2020; Lupi et al., 2020), which is convenient when the aim is comparing specific policy settings.

Our study belongs to the second type of approach. We analyse the economic and environmental impacts of farm management practices scenarios employing the Soil and Water Assessment Tool (SWAT; Neitsch et al., 2011), a spatial and dynamic biophysical model at the basin scale. We compute the effects of changes in the area under supplemental irrigation and fertiliser application rates on a set of SWAT output variables such as crop yields and water quality indicators, namely nitrates and phosphorus concentrations. These output variables, crop prices and other economic variables are then inputted into an economic model of decisions under uncertainty to evaluate the impacts on economic benefits and water quantity and quality of each proposed scenario of agricultural intensification pathways. These scenarios are compared with the baseline or benchmark consisting of rain-fed agriculture and business-as-usual fertiliser rates.

We make at least two other contributions to this literature. First, our model of decisions under uncertainty allows us to disentangle the portion of economic benefits due to changes in expected returns from those resulting from reduction in their volatility. This goes beyond previously cited studies that focus only on the expected returns. Second, the trade-offs between economic benefits and water quality are assessed by means of a set of ratios that show the amount of money that producers need to give up to increase water quality by one unit. In a context of lacking economic valuations of environmental characteristics of water bodies, these results provide useful information for policymakers for assessing water resource quantity and quality at the basin level, as well as economic factors that influence them.

To show the appropriateness of the approach in tackling the two main issues around water (quantity and quality), and their interaction with the economic activities within the basin, we calibrate and run the model and the scenarios on a particular basin of the temperate region of South America. This basin of the San Salvador River in Uruguay is characterised by the expansion of agriculture along both the extensive and intensive margins, the growth of urban areas and industrial development, and as a result, an increasing pressure on water resources (Hastings et al., 2020; MVOTMA, 2017). The scenarios implemented replicate two of the main challenges in the basin. One is the expansion of supplemental irrigation driven by the high-productivity soils, the prospects of developing additional water sources (through dams or reservoirs) and the tax incentives to invest in irrigation developments. The other is that farmers seek to increase row crop yields by applying higher fertiliser rates when using irrigation to avoid nitrogen and phosphorous being limiting factors, but with potentially unintended consequences on water quality.

From a more local perspective, and to the best of our knowledge, this is the first application of the IAM approach in the case of Uruguayan agriculture. Our results are a key input for environmental regulators to monitor the compliance of the existing nutrient concentration thresholds in water bodies and how they relate to the intensification practices carried out in the basin. Also, the results are relevant for agricultural policymakers to assess the effects on the economic benefits of higher fertiliser application rates and the expansion of irrigation when constrained by specific environmental regulations. Market or non-market instruments (taxes and subsidies, or command and control) to change farmers' incentives to use fertiliser or irrigation can be evaluated, quantified and monitored with the proposed model. Furthermore, our scenarios can provide insights to stakeholders in other basins that experience similar challenges from their own crop intensification processes. While we illustrate with an application to a particular river basin, these methods can be readily applied to other basins, provided a calibrated SWAT model is available.

We explain the model in the next section. Section 3 is devoted to the description of the basin and the implementation of the scenarios. We present results in Section 4 and a conclusion in Section 5.

2 | THE MODEL

This model aims to choose the set of farm management practices, including supplemental irrigation levels, fertiliser rates and crop sequences over time that provide the maximum economic benefits at the aggregate basin level, among several feasible alternatives. While the more intensive practices are often associated with higher crop yields, these do not necessarily maximise profits and are also potentially associated with higher adverse effects on water quality. The latter can be due to, for example, increased soil erosion, run-off and nutrient concentration levels in water bodies. Hence, an appropriate assessment model must be able to capture both the economic and environmental outcomes simultaneously. Below, we describe the economic and biophysical models and their integration.

Consider utility as a function of the per-hectare profits of the ith production unit, $U(\pi_i)$. Per-hectare profits are computed as crop revenues minus costs, as shown in Equation (1). Revenues in Equation (2) are the yield of crop j (measured in tons per-hectare, tonne/ha) times the price (in dollars per tonne, \$/tonne) and aggregated over the J crops in unit i. Costs in Equation (3) are the sum over the costs of the J crops in that unit, which include the expenditures on fertiliser, the expenditures on irrigation and the expenditures on the remaining inputs (seeds, pesticides, labour and machinery services) summarised by C_{ij}.

$$\pi_i = \text{Revenue}_i - \text{Cost}_i \tag{1}$$

$$\text{Revenue}_i = \sum_{j=1}^{J} \text{Yield}_{ij} \times \text{Price}_j \tag{2}$$

$$\text{Cost}_i = \sum_{j=1}^{J} \left[\text{Fert}_{ij} \times \text{Price}_{\text{Fert}} + \text{Water}_{ij} \times \text{Price}_{\text{Water}} + C_{ij} \right] \tag{3}$$

Profits of each production unit i are uncertain since they are affected by random variables in the revenue equation (crop yields) and in the cost equation (quantity of water needed for irrigation). In our model, yields and water use are a function of climate conditions (e.g., precipitation, temperature, evapotranspiration and solar radiation). They are the output of the structural biophysical model, as we explain below. While output prices are also random, we assume the decision-maker considers prices at their expected values, and therefore, they do not contribute to the randomness of profits. We assume that input prices are fixed because they are known when production decisions are made.

Profit uncertainty determines a problem in which producers located in production unit i face a lottery on profits. As they tend to be risk-averse, they will place value on risk-reducing technologies, such as the use of supplemental irrigation, as it reduces the income volatility relative to rain-fed production via more stable crop yields (Apland et al., 1980; Pandey, 1990; Shi et al., 2019). An appropriate methodology to tackle the problem in this context is the expected utility approach, which we instrument by using an exponential utility function of profits:

$$U\left(\pi_i\right) = -e^{-\alpha \pi_i} \tag{4}$$

This is a continuous, concave and monotone function. A measure of the Arrow–Pratt absolute risk aversion level can be obtained as the ratio of the second to the first derivative, as in Equation (5).

$$\alpha = -\frac{U''\left(\pi_i\right)}{U'\left(\pi_i\right)} \tag{5}$$

To account for the economic benefits in production unit i given the uncertain nature of profits, we rely on the concept of certainty equivalent, CE_i, defined as the sure amount of money the decision-maker in each unit i is willing to accept to avoid the uncertainty of the lottery but maintaining the same level of expected utility. It can be shown that it equals the expected value of the lottery $E(\pi_i)$ minus its risk premium (RP_i).[1] This premium represents how much money an agent is willing to pay to avoid the risky lottery holding the same level of expected utility. Thus, a higher CE_i can arise for a given production unit due to higher expected profits, lower risks or both. Throughout this study, it is regarded as our measure of the economic benefits. For an exponential utility function as in Equation (4), and for each production unit i, it is computed as in Equation (6).

$$\mathrm{CE}_i = -\frac{1}{\alpha}\log\left[E(e^{-\alpha \pi_i})\right] \tag{6}$$

Finally, we compute the per-hectare certainty equivalent at the basin level CE by adding up the CE_i of each production unit i weighted by their area in hectares (h_i) and divided by the total area of the basin.

$$\mathrm{CE} = \frac{\sum_{i=1}^{I} \mathrm{CE}_i \times h_i}{\sum_{i=1}^{I} h_i} \tag{7}$$

Biophysical variables that enter the economic model, such as crop yields, quantity of fertilisers and water for irrigation, come from the structural biophysical SWAT model.

[1]The certainty equivalent CE_i is defined such that $U(\mathrm{CE}_i) = E(U(\pi_i))$. Then, solving for CE_i, we obtain $\mathrm{CE}_i = U^{-1}(E(U(\pi_i))) = E(\pi_i) - \mathrm{RP}_i$.

The SWAT is a river basin scale model based on geographic information system (GIS) input data, which simulates biophysical processes (e.g., plant growth, evapotranspiration, soil erosion, run-off and leaching) into a series of decision-making units called 'Hydrological Response Units' (HRU). Each HRU is unique and represents a homogeneous type of land use and soil within a sub-basin, where each sub-basin may contain one or more HRUs. This model reports as output variables, physical quantities of production in each HRU and water quality results for a number of spatially distributed modelled streams within the basin. Crop growth is simulated in SWAT with the Environmental Policy Integrated Climate (EPIC) structural model (Williams et al., 1989) using a set of equations and calibrated parameter values unique for each crop. For each HRU, the model simulates biophysical processes such as leaf interception of solar radiation, biomass conversion, biomass division into roots, above-ground mass and yield, root growth, water use and nutrient uptake. Crop growth begins with planting at the specified day and month and with the specified number of heat units required to reach maturity. Biomass production is computed daily as a function of soil physical and chemical characteristics, farm practices (tillage, fertiliser, pesticides and irrigation) and climate variables (relative humidity, precipitation, potential evapotranspiration and solar radiation). Crop yields are computed as a fraction of the total biomass produced (harvest index), leaving the rest as crop residues that continue their biological process in the soil. Yield is recorded on the harvest date and is considered as that year's output. This generates a distribution of yields for each HRU that is spatially correlated.

This model has been widely used to analyse the impact on water quantity and quality caused by land use and farming practices (Gassman et al., 2007).[2] In recent years, Uruguayan authorities and research groups have made significant efforts to implement, calibrate and validate this model for various relevant basins in the country (Mer et al., 2020).[3] Our study capitalises on these endeavours.

Biophysical output variables (namely yields, quantity of fertilisers and water for irrigation) that are simulated by SWAT are plugged into Equations (1)–(3). More specifically, in Equations (1) and (2), we input crop yields, fertiliser and supplemental irrigation rates, such that conditional on output and input prices, we can evaluate the economic impact of the set of farming practices we intend to analyse.

To assess their environmental impact on water quality, we rely on a set of indicators defined by the environmental regulator. For example, we obtain daily water concentration levels of nitrates (NO_3, which we denote by N to save on notation) and phosphorus (P) and compute the proportion of time that the concentration level is above the threshold given by the regulator. As shown in Equations (8) and (9), we compare the concentrations with the environmental threshold (TN and TP) such that if the level of N and P is higher than this threshold, the indicator variables (IN and IP) take the value of 1, and 0 otherwise. These variables are outputs of the SWAT model and are computed at the basin outlet.

$$\mathrm{IN}_t = \begin{cases} 1 & \text{if} \quad N_t \geq \mathrm{TN}_t \\ 0 & \text{if} \quad N_t < \mathrm{TN}_t \end{cases} \tag{8}$$

$$\mathrm{IP}_t = \begin{cases} 1 & \text{if} \quad P_t \geq \mathrm{TP}_t \\ 0 & \text{if} \quad P_t < \mathrm{TP}_t \end{cases} \tag{9}$$

[2]A comprehensive list of journal articles and studies employing the SWAT model can be found here: https://www.card.iastate.edu/swat_articles/

[3]For example, the 'Grupo Interinstitucional de Herramientas de Modelacion para la Gestion de la Cantidad y Calidad de Agua – GmicUy' https://proyectoinia-iri-usyd.github.io/GmicUy/antecedentes.html

Thus, by adding up the indicator variables and dividing up by the number of simulated days (T), as in Equations (10) and (11), we obtain the proportion of time in which the environmental indicators defined by regulation are violated (i.e., the thresholds are exceeded).[4]

$$\text{PropN} = \frac{\sum_{t=1}^{T} \text{IN}_t}{\text{T}} \tag{10}$$

$$\text{PropP} = \frac{\sum_{t=1}^{T} \text{IP}_t}{T} \tag{11}$$

Finally, to evaluate the economic and environmental impacts of the mentioned farming practices and land uses, we run the model with a set of scenarios that are compared with a baseline. We explain the baseline and the scenario design in the next section. We are interested in assessing the trade-offs between economic benefits and water quality levels. To this end, we compute the indices given in Equations (12) and (13), which show the change of the aggregated certainty equivalent relative to the baseline scenario, ΔCE, due to the change in the median concentration of N and P at the basin outlet.

$$\lambda = \frac{\Delta \text{CE}}{\Delta N_{\text{median}}} \tag{12}$$

$$\kappa = \frac{\Delta \text{CE}}{\Delta P_{\text{median}}} \tag{13}$$

Hence, using Equations (12) and (13), we measure by how much the CE changes when the median concentration levels of nitrates and phosphorous deteriorate by one unit. We choose to report these ratios with respect to the median to account for the asymmetries and extreme values of daily nutrient concentration levels caused by the combination of low precipitations, low stream flows and high nutrient export levels to the catchment.

3 | STUDY AREA, PROPOSED SCENARIOS AND DATA

The San Salvador River basin belongs to a major agricultural area in the Southwest region of Uruguay characterised by a smooth hilled landscape under a humid subtropical climate and with an average precipitation of 1100 mm/year. Since 1990, but mainly after the 2000s, this basin was a subject to an intensification process of fast-growing crop areas with soybeans, corn, wheat and barley as the main crops, which generally substituted native grasslands (Hastings et al., 2020). Despite showing a high inter-annual rainfall variability, most of its area is under rain-fed crop production. Supplemental irrigation is an attractive technology for farmers since it can potentially increase crop yields and simultaneously reduce their volatility (Failde et al., 2013; Montoya et al., 2017; Montoya & Otero, 2019; Rosas & Sans, 2023). However, intensification of crop production leads to increasing concern since it tends to add more pressure on water resources (Baker, 2006). More specifically, since 2014, environmental authorities (MVOTMA, 2017) have found nitrogen and phosphorous concentrations at the basin's outlet above the regulation's threshold (1 mg/L and 0.0025 mg/L,

[4]The number of days T corresponds to the 20 years for which the biophysical mode is run. More on this in the description of the SWAT runs in the next section.

TABLE 1 Representative crop sequences in the San Salvador River basin, Uruguay.

Crop seq.	Year 1		Year 2		Year 3		Area
1	Oats	Corn	Oats	Soybean			18.6%
2	Oats	Soybean	Oats	Soybean	Oats	Corn	25.0%
3	Pasture	Soybean	Oats	Soybean			37.4%
4	Wheat	Soybean 2	Oats	Soybean			12.5%
5	Barley	Soybean 2	Wheat	Soybean 2			0.2%
6	Wheat	Soybean 2	Oats	Corn	Oats	Soybean	6.3%

Note: (1) Soybean 2 means soybean as a second crop. (2) In each year, the first column indicates the winter crop, and the second column the summer crop.

respectively). Furthermore, since water pollution in this basin is mainly due to nonpoint sources, accounting for over 90% of the nitrates and phosphorus discharges, modelling and assessing fertilisation, irrigation and other crop practices are key to understanding and reducing nutrient exports.

Table 1 shows the six crop sequences that can be considered representative of the farming crop systems in the catchment and are in line with the soil use regulations in place. Crop sequences comprise both summer crops (soybean and corn) and winter crops (wheat, barley, oats and pasture) during either 2 or 3 years. We evaluate the economic and environmental impacts of typical farm management practices by means of a set of nine (3×3) scenarios constructed with three supplemental irrigation levels and three fertiliser rates, all compared with a baseline scenario of rain-fed and observed fertiliser rates.

Supplemental irrigation may be applied to the summer crops (soybean and corn) in crop sequences 1 and 6 because they are regarded as the most profitable due to their large share of corn and soybeans as first crop, that is, when they come after a cover crop and not after a winter crop. We implement the three scenarios by simulating irrigation in both crop sequences (which cover 25% of the basin area), only in crop sequence 1 (18.9% of the basin) and only in crop sequence 6 (6.3% of the area). The irrigation application on each HRU is simulated in SWAT using an automated routine that applies irrigation whenever a given water stress threshold is reached. Water stress in an HRU is measured as the ratio of evapotranspiration (ET) to the potential evapotranspiration (PET), as shown in Equation (14). In this equation, 1 is the maximum water stress level, while 0 represents no deficit (evapotranspiration equals its potential). Consistent with the literature (Montoya et al., 2017; Montoya & Otero, 2019) and recommendations from farm extension and technical advisors, the threshold was set equal to 0.8, meaning that at least 80% of the crop's water demand is satisfied. In this line, the irrigation rate is endogenously determined within the SWAT model.

$$\text{Stress} = 1 - \frac{\text{ET}}{\text{PET}} \tag{14}$$

To implement the fertiliser application scenarios, we simulate a (low, medium or high) increase in fertiliser rates in irrigated areas relative to the observed rates in rain-fed crop systems. The latter are 200 kg/ha of standard urea, 150 kg/ha of diammonium phosphate and 46 kg/ha of urea 46-00-00. These rates were obtained from extension and technical advisors and are consistent with rates in farm operations in the basin. The medium increase scenario is calibrated to match current practices in irrigated plots, which are 275 kg/ha of standard urea, 190 kg/ha of diammonium phosphate and 53 kg/ha of urea 46-00-00. Then, high and low fertiliser scenarios are set by adding or reducing 50% of the difference between the medium and rain-fed scenarios. While scenarios of increasing fertiliser rates in rain-fed crop systems are of

TABLE 2 Irrigation and fertiliser rate scenarios.

Scenario	Irrigated Crop sequences	Δ fertiliser rate	Irrigated area (% of the basin)
1	1 and 6	High	25.3%
2	1 and 6	Medium	25.3%
3	1 and 6	Low	25.3%
4	1	High	18.9%
5	1	Medium	18.9%
6	1	Low	18.9%
7	6	High	6.3%
8	6	Medium	6.3%
9	6	Low	6.3%
10	None	Observed	0%

TABLE 3 Crop prices and costs for irrigation and fertilisation scenarios.

		Input cost by fertilisation scenario (kg/ha)			
Crop	Price ($/ton)	Base	Low	Medium	High
Soybean (1st)	310	488	496	504	512
Soybean (2nd)	310	395	401	406	412
Wheat	140	476	504	531	559
Barley	140	539	568	599	628
Corn	185	694	733	773	813
Oats	195	393	415	436	458

Note: Values in 2019 $/ha. Source: Cámara Mercantil de Productos del País, Uruguay.

interest and will be considered in further research, in this analysis, we highlight their interaction within irrigated agriculture. Additionally, the limited substitutability among nitrogen and phosphorus motivated the scenarios with increments in the same proportion. The same resaon led us to avoid consisting scenarios of expansions of a single nutrient.

Combining irrigation and fertiliser practices on the two irrigated crop sequences considered, we obtain the nine (3×3) scenarios plus the baseline (Table 2). This allows us to assess the economic and environmental impacts of one intensification practice holding constant or changing the other. As Table 2 indicates, we included discrete changes in the area under irrigation reflecting the current land uses under crop sequences for which this technology is appropriate. While simulations for additional scenarios of varying proportions of the basin under irrigation could be performed, this would have unnecessarily complicated the implementation without modifying our message.

Table 3 shows crop prices and costs that are used in the economic model, all calibrated to 2019 values. Crop prices come from the Cámara Mercantil de Productos del Pais, a chamber of agricultural exporters that reports prices (in $/tonne) for all the required crops. Prices are adjusted by a transportation cost of 10 $/tonne (to avoid assuming a given yield in its computation) based on the distance to a relevant export port. This would be equivalent to using farm-gate prices, already adjusted for transportation costs. We require crop-specific input costs with the itemisation of some categories, such as fertiliser and irrigation costs, and also providing both the quantity and the price of these inputs. These are collected from farmers operating in the basin and are within the range of values from other sources in that region that publish aggregate input costs. The cost of water for irrigation was assumed to be 0.65 dollars per millimetre ($/mm), according to expert judgement from the National Institute of Agricultural Research (INIA).

As there are no empirical studies estimating the absolute risk aversion coefficient for Uruguayan farmers, in this study, we evaluated the utility function in six values that are consistent with relative risk aversion coefficients in the range of 0.5 and 4, as proposed by Anderson and Dillon (1992). This strategy follows the literature on modelling and calibrating the negative exponential utility function (Babcock et al., 1993; Hardaker et al., 2004, 2015), and additionally, this range contains the estimation of this parameter for the Uruguayan and other Latin American countries' general population (Gandelman & Hernandez-Murillo, 2015). This range allows us to perform the stochastic efficiency with respect to a function (SERF) method from Hardaker et al. (2004), a method to rank scenarios by considering different risk preferences. According to this method, we define a scenario as risk-efficient or optimal for a given absolute risk aversion level when it has the highest CE.

SWAT model parameters were calibrated to replicate observed historical data in the Salvador River basin, obtained from official agricultural and environmental statistics and farm-level data. We run the SWAT model on daily time steps for 20 years. We treat an HRU defined within SWAT as a production unit. We input the required variables in the economic model (i.e., yield distributions, cost structure, prices and nutrient concentrations), and using Equations (6)–(13), we compute the CEs, the nutrient level concentrations, the proportion of days above the thresholds and the indices measuring the trade-offs between the economic and environmental results. The yield distribution constructed with a yearly time series that drives the profit distribution is not autocorrelated but constructed with independent draws because while daily biomass production is autocorrelated (due to the daily weather variables), it is not autocorrelated on an annual basis. Box–Pierce autocorrelation tests on profit distributions do not reject the null hypothesis of the absence of autocorrelation.

4 | RESULTS

This section presents the model assessment results. Subsection 4.1 shows the economic results. Subsection 4.2 presents the environmental/water quality results, and Subsection 4.3 shows the trade-offs between economic and environmental results.

4.1 | Economic results

4.1.1 | Expected profits

Table 4 presents the results for each of the proposed scenarios at the basin level. It shows the per-hectare expected profits $E(\pi)$ in $/ha/year and their percentage change relative to the rain-fed baseline scenario. Results show that the use of supplemental irrigation in larger portions of the basin increases expected profits and that the highest increase is for those scenarios of low increments of fertiliser rates with respect to the observed rates. The latter occurs because medium and high marginal changes in fertiliser costs exceed the marginal revenue due to yield improvements. In the rain-fed baseline scenario, expected profits are 257 $/ha/year. When supplemental irrigation is applied to crop sequence 6 (6.3% of the basin area), the expected profits increase by up to 6.3% under a low fertilisation level. When irrigation is expanded to a larger area of the basin, for example, when it is applied to crop sequence 1, which comprises 18.9% of the catchment area, the expected profits increase by

TABLE 4 Expected profits ($/ha/year) by scenario.

Scenario	Irrigated rotations	Fertilisation	Expected profit $/ha	Change w.r.t base.	Irrigated area (% of basin)
1	1 and 6	High	305.96	18.95%	25.3%
2	1 and 6	Medium	320.23	24.50%	25.3%
3	1 and 6	Low	330.83	28.62%	25.3%
4	1	High	297.21	15.55%	18.9%
5	1	Medium	307.22	19.44%	18.9%
6	1	Low	314.69	22.33%	18.9%
7	6	High	266.00	3.41%	6.3%
8	6	Medium	270.27	5.07%	6.3%
9	6	Low	273.43	6.30%	6.3%
Base	None	Observed	257.22	–	0%

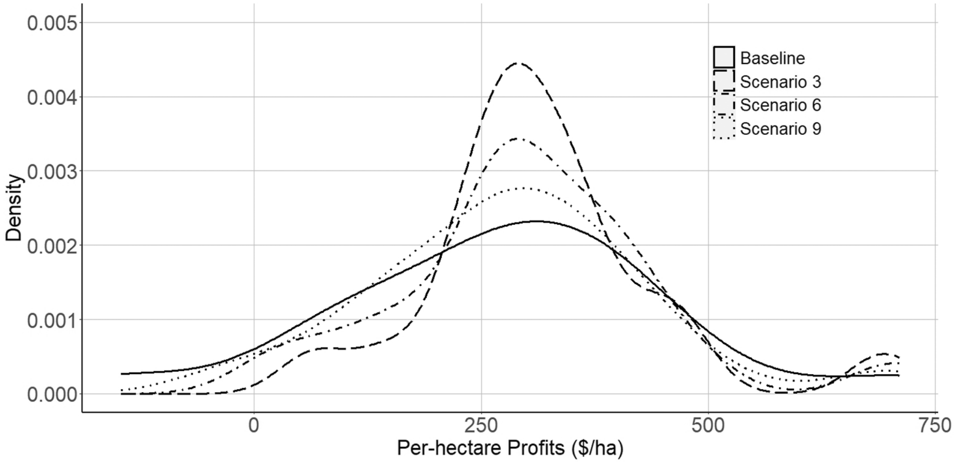

FIGURE 1 Kernel density functions of per-hectare profits ($/ha) for selected scenarios and for selected scenarios and medium fertilisation.

up to 22.3%. Lastly, when irrigation is applied in both crop sequences (25.3% of the basin area), net expected profits increase by up to 28.6% relative to the baseline. Note that by holding the crop sequences constant, all the changes in expected profits can be attributed to the increases in the proportion of the basin that is irrigated and the change in the fertilisation rate of the different scenarios.

Figure 1, which depicts the distribution of simulated profits per year for the whole basin for selected scenarios, shows that Scenario 3, that is, the one with the most extensive irrigation area, accumulates more mass around the centre of the distribution than those with lower area or the baseline rain-fed scenarios. In the latter, this lower mass is allocated to fatter left tails of the respective densities. This is mainly explained by dry years, which allow supplemental irrigation to reduce crop water stress and, thus, prevents significant yield losses. In other words, this figure illustrates not only the increase in expected profits but also a reduction in the variability around mean profits as a larger area is devoted to irrigation. These are the main drivers of the results we explain below.

TABLE 5 Certainty equivalent by scenario and risk aversion level.

	Absolute risk aversion coefficient (ARA)					
Scenario	**0**	**0.0019**	**0.0039**	**0.0078**	**0.0117**	**0.0156**
1	306	278	253	213	185	164
2	320	293	268	228	198	176
3	331	303	277	235	204	179
4	297	262	229	180	146	121
5	307	272	240	191	156	130
6	315	280	247	197	161	133
7	266	234	202	144	96	59
8	270	238	206	148	99	62
9	273	241	208	149	100	62
Base	257	218	179	111	57	16

4.1.2 | Simulated certainty equivalent

When we consider the risk aversion of the economic agents, the economic effects in the scenarios analysed are driven both by the changes in expected profits and in their volatility. To compare the economic benefits across scenarios, we use the CE in Equation (7) given a risk aversion level (ARA parameter α).

Table 5 displays the CE results for the different levels of risk aversion reported in Section 3.[5] For a moderate risk aversion level (e.g., ARA equal to 0.0039), all scenarios yield a positive value of the aggregate CE of Equation (7). For example, in the baseline rain-fed scenario, the CE is 179 \$/ha, and it increases as irrigation is extended to larger shares of the basin area. Furthermore, for a given share with irrigation, scenarios with low increases in fertiliser application rates (3, 6 and 9) yield the highest CE, implying that higher and more stable yields do not compensate for the higher fertiliser cost. According to the SERF method and for all levels of risk aversion (Figure 2), Scenario 3 is the most risk-efficient, that is, when irrigation is applied to both crop sequences, yielding a CE of 277 \$/ha. Figure 2 also shows that the curves do not cross, implying that this is the dominating scenario for all levels of risk aversion.

The comparison to the risk-neutral case (i.e., the second column of Table 5) allows us to assess the role of expanding irrigation and changing fertiliser rates in reducing the variability of uncertain profits. The difference between the two columns is the risk premium, that is, the amount of money the agent is willing to pay to avoid uncertainty while maintaining the same expected utility level. Again, when comparing a moderate risk aversion level (ARA equal 0.0039) to the risk-neutral case, it can be seen that the rain-fed scenario (the case with the highest volatility) is consistent with a relatively high RP of 78 (=257–179) \$/ha. Nevertheless, on the other extreme, in Scenario 3, with the highest share of irrigation area, the RP is significantly lower, 54 (=331–277) \$/ha.

As expected, CE decreases with higher levels of risk aversion within each scenario. As stated in Equation (6), this reflects the fact that risk-averse individuals would pay higher risk premiums to avoid the lottery. On the other hand, at the same level of risk aversion, scenarios with irrigation on either or both crop rotations reduce the risk premium. Therefore, the CE

[5]The previous results about expected profits are the limiting case of risk-neutral agents (ARA parameter equal to zero). Therefore, the column ARA = 0 concurs with the column 'Expected Profits \$/ha' in Table 4.

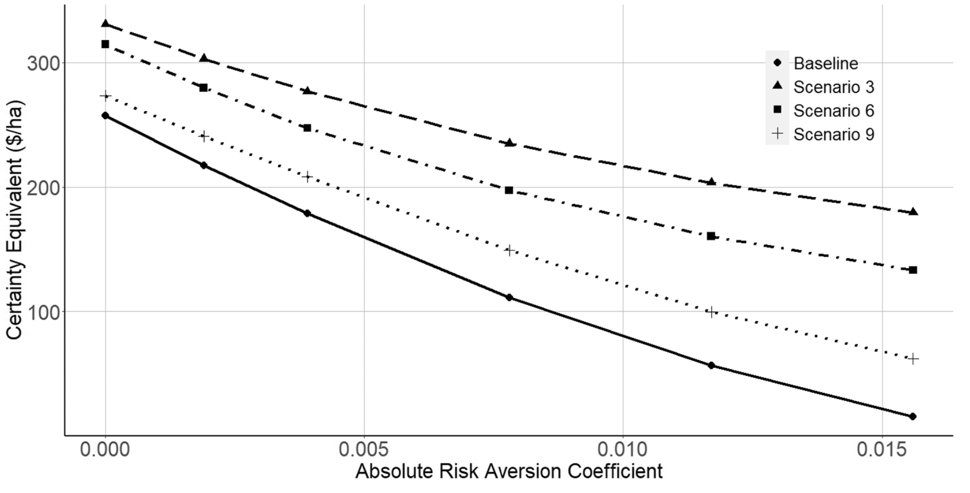

FIGURE 2 Certainty equivalent ($/ha) by the level of risk aversion and for selected scenarios.

increases with respect to that of the rain-fed scenario. The magnitude of this difference grows as the level of risk aversion increases.

The difference in the CE between irrigation scenarios and the rain-fed scenario illustrates the role of supplemental irrigation in reducing the uncertainty of profits. While larger areas under irrigation could induce improvements of up to 74 $/ha (=331-257) via higher expected profits, improvements due to risk premium reductions could be sizable. For example, in the same scenario and for a moderate risk aversion level (ARA parameter of 0.0039), the CE improvement is as high as 98 (=277–179) $/ha, of which about one-fourth is due to risk premium reduction from the use of irrigation (24 = 277-179-74 $/ha). This risk premium is driven by the higher volatility of profits with respect to irrigation scenarios, and particularly, the volatility is exacerbated in dry years when crop yields are affected by water stress. In more extreme cases, ARA equals 0.0117, for example, and for the same scenarios, economic benefits via risk premium reductions account for approximately the same amount of the total CE increase as the expected profits increase (73 = 204-57-74 $/ha).

4.2 | Environmental results

Environmental results are assessed by computing nitrate (NO_3) and phosphorus (P) concentration levels at the basin's outlet. Table 6 reports, for each scenario, the mean and median concentration levels of NO_3 and P in water and the percentage of days in which the environmental threshold is surpassed.

In the case of NO_3, in the rain-fed scenario, the mean concentration level is 3.11 mg/L, while the median value is 1.26 mg/L. These results are in line with those reported by the Ministry of the Environment (MVOTMA, 2017). In the most input-intensive scenario, where irrigation is applied on both crop sequences and the increase in fertiliser rates is high, the mean value increases up to 3.58 mg/L and the median to 1.40 mg/L, or respectively, 15.11% and 11.11% relative to the baseline.[6] The environmental threshold for NO_3 concentration established by the regulator (1 mg/L) is breached in 53.74% of the days in the rain-fed baseline scenario. In the most

[6]The difference between the mean and the median is driven by the skewness of the distribution due to the existence of extreme maximum values of the variable (e.g., as high as 242 mg/L in Scenario 9, which is mainly explained by low simulated flows).

TABLE 6 Nitrates (NO_3) and phosphorus (P) concentrations at the basin outlet.

Scenario	Mean NO_3 mg/L	Median NO_3 mg/L	Δ median NO_3	NO_3 Viol	Mean P mg/L	Median P mg/L	Δ median P	P Viol
1	3.58	1.40	11.11%	57.92%	0.0072	0.0051	13.24%	<1.00%
2	3.44	1.36	8.54%	57.50%	0.0072	0.0050	13.06%	<1.00%
3	3.32	1.34	6.91%	57.50%	0.0072	0.0050	12.68%	<1.00%
4	3.39	1.33	6.02%	55.83%	0.0071	0.0050	11.10%	<1.00%
5	3.34	1.33	5.82%	55.83%	0.0071	0.0049	10.56%	<1.00%
6	3.24	1.33	5.66%	55.83%	0.0071	0.0049	10.39%	<1.00%
7	3.29	1.31	4.18%	56.25%	0.0070	0.0046	2.87%	<1.00%
8	3.25	1.30	3.79%	55.83%	0.0070	0.0046	2.87%	<1.00%
9	3.22	1.30	3.48%	55.83%	0.0069	0.0046	2.91%	<1.00%
Base	3.11	1.26	–	53.75%	0.0068	0.0045	–	<1.00%

input-intensive scenario, this value reaches 57.92%, which implies an increase of 7.75% with respect to the rain-fed scenario.

In the case of P, Table 6 indicates that in the most input-intensive land use scenario (Scenario 1), the mean P concentration increases by 5.81% (0.0072/0.0068) while the median increases by 13.24% with respect to the rain-fed scenario. However, contrary to the nitrates case, the threshold is breached in less than 1% of the days for all scenarios.

4.3 | Trade-offs between economic and environmental results

As noted in Section 4.1, intensification through irrigation and fertilisation practices tends to increase producer's yield and economic benefits. Simultaneously, this phenomenon could bring higher nutrient (NO_3 and P) concentration levels driven by the higher use of nitrogen and phosphorus and their relationship with other biophysical processes such as soil erosion, surface run-off and leaching. Results of the marginal impacts on the per-hectare CE from an increase in the median nutrient concentration of NO_3 and P (Equations (12) and (13), respectively) are presented in Tables 7 and 8. The value placed in each cell indicates the marginal increase in the CE per unit of increase in the nutrient concentration level, for a given scenario and risk aversion level. Changes in each scenario are measured with respect to the baseline.

As shown in Table 7, the trade-off between the CE and the median nitrate concentrations is greater for Scenarios 3 and 6 for all levels of risk aversion. These scenarios consist of a low increase in fertiliser application rates. The highest value is achieved in Scenario 3, where the increase in one unit of median nitrate concentration could yield an increase in the CE of 14.18 $/ha for a moderate value of risk aversion (ARA parameter of 0.0039). Due to changes in the CE (numerator), we observe a monotone increase in this ratio as risk aversion grows.

In the case of phosphorus concentration levels, we also find that the scenarios consisting of low increments of fertiliser application rates give the highest increments in the CE due to a unit increase in the median phosphorus concentration level. However, conditional on having low fertiliser rate increases, the scenarios of lower shares of the basin with irrigation (Scenarios 7, 8, and 9) show the highest increases in CE per unit increase of phosphorous concentration. In particular, Scenario 9 of low fertiliser rate increments achieves the highest CE increase, for example, 10.16 $/ha for a moderate level of risk aversion (ARA parameter of 0.0039).

These results show that scenarios of medium and high increases in fertiliser application rates do not have a good relative economic and environmental performance because they are

TABLE 7 Trade-off ratios between economic benefits and median nitrates concentration levels.

	Absolute risk aversion coefficient					
Scenario	**0**	**0.0019**	**0.0039**	**0.0078**	**0.0117**	**0.0156**
1	4.39	5.48	6.64	9.14	11.54	13.37
2	7.38	8.85	10.40	13.61	16.59	18.77
3	10.65	12.37	14.18	17.88	21.26	23.67
4	6.64	7.32	8.36	11.43	14.84	17.49
5	8.59	9.42	10.57	13.73	17.08	19.61
6	10.15	10.98	12.11	15.15	18.36	20.74
7	2.10	4.02	5.64	7.85	9.34	10.38
8	3.44	5.49	7.23	9.62	11.19	12.23
9	4.66	6.72	8.50	10.89	12.40	13.33

TABLE 8 Trade-off ratios between economic benefits and median phosphorus concentration levels.

	Absolute risk aversion coefficient					
Scenario	**0**	**0.0019**	**0.0039**	**0.0078**	**0.0117**	**0.0156**
1	3.68	4.60	5.57	7.67	9.68	11.22
2	4.82	5.79	6.80	8.90	10.85	12.27
3	5.81	6.74	7.73	9.74	11.59	12.90
4	3.60	3.97	4.53	6.20	8.05	9.49
5	4.74	5.19	5.83	7.57	9.41	10.81
6	5.53	5.98	6.59	8.25	10.00	11.30
7	3.06	5.86	8.21	11.43	13.61	15.12
8	4.55	7.24	9.55	12.70	14.77	16.15
9	5.57	8.04	10.16	13.03	14.82	15.94

dominated by scenarios of low increments of fertiliser rates (Scenarios 3, 6 and 9), both in the case of nitrate concentration and phosphorous concentration levels. On the other hand, conditional on low increments of fertiliser rates, the impacts on nutrient concentration levels of the expansion of supplemental irrigation are mixed. While in the case of nitrate concentration levels, the scenarios of high expansion of irrigation (Scenario 3) outperform CE increases in those with low or moderate irrigated areas, in the case of phosphorous concentrations, those with low expansion of irrigation are the dominating scenarios (Scenario 9). In other words, we find that as we increase the area with irrigation, the CE increases faster than the nitrate concentration level. However, the CE does not increase as fast as the phosphorous concentrations.

However, we note that both the increase in fertiliser rates and the irrigation expansion affect marginally (or not at all) the percentage of days that the N and P concentration thresholds are violated (see the 5th and 9th columns of Table 6). This is a relevant result from the environmental management point of view because it implies that these intensification farm practices have a positive economic impact with an environmental impact not very different from that of a less intensive practice (rain-fed production). Economic instruments to promote these practices should take this into account.

5 | CONCLUSIONS

The growing global demand for food, fibre and fuels imposes significant challenges on agriculture because it requires increasing supply, which can lead to additional pressures over natural resources. These global drivers affect incentives of economic agents at the local level through markets, prices and other channels, typically leading to increases in agricultural output but with consequences on specific dimensions of the environment such as water, soil and air. Water use in agriculture faces competition from other sources of water demand (manufacturing, mining and municipal use), and in turn, they all contribute to changes in its quality levels. Moreover, both quantity and quality impacts are time- and space-dependent, which imposes additional challenges for water management.

In this context, the sustainable management of water resources by regulating authorities requires paying close attention to land use, farmers' behaviour and practices, competing activities for water demand and the performance of environmental indicators within the basin. The appropriate set of tools to analyse these issues requires the ability to assess all these drivers simultaneously. The fact that their consequences are local implies that approaches at the basin scale are one way of dealing with the problem.

In this study, we integrate a biophysical hydrological model at the basin scale that allows for spatial and time heterogeneity with an economic model of decisions under uncertainty to simultaneously analyse the production, economic and environmental effects of agricultural activities carried out in a basin. Uncertainty comes from climatic variables driving yields (e.g., precipitation, temperature, evapotranspiration, solar radiation and water availability for irrigation) and irrigation costs, which directly translates into uncertainty in farm profits. Environmental impacts are evaluated by means of the nutrient concentration levels in water bodies, while production and economic impacts are assessed through the economic benefits of these agricultural activities. The introduction of uncertainty in the decision-making process allows us to evaluate the economic impacts due to changes not only in expected profits but also in their volatility. Furthermore, the integrated model can tackle the trade-offs between economic benefits and water quality impacts through a set of indicators endogenously determined within the model.

Within the IAM literature, we integrate the SWAT, a widely used biophysical simulation model, with an economic model based on expected utility theory, showing an application in one of the most important agricultural basins in Uruguay. Our focus is the assessment of the economic and environmental impacts of crop intensification practices employed by farmers who respond to incentives of output expansion. At least two contributions to this literature arise from implementing this model. First, by employing the concept of CE for a given level of risk aversion, we assess the economic benefits driven by both the higher expected yields and those coming from the lower yield volatility of the crop practices analysed. Our study departs from the previous literature, which focussed only on the average effects. Second, we evaluate the trade-offs between economic benefits and water quality levels by means of a set of indicators computed with variables endogenously determined within the model, which show the amount of money that farmers are expected to give up to increase water quality levels by one unit.

The model is calibrated to the San Salvador River basin located in the southwest region of Uruguay, which, with an area of about 240,000 hectares, accounts for about 21% of the wheat, 17% of the corn, 9% of the soybean and 14% of the sorghum produced in the country. We specify a set of nine (3×3) scenarios combining different levels of the area under supplemental irrigation (6.3%, 18.6% and 25.0% of the basin area) with different degrees of increments in fertiliser application rates (low, medium and high). These agricultural intensification scenarios replicate typical land management practices encountered in this region that farmers apply to increase output along the intensive margin. The scenario results are compared against a baseline of rain-fed production and observed fertiliser application rates typical of rain-fed crop systems.

Results show an estimated expected profit of 257 $/ha in the baseline rain-fed agriculture. Expected profits increase up to 330 $/ha, mainly driven by expanding supplemental irrigation to larger shares of the basin area. Furthermore, for a given area under irrigation, scenarios of low increments in fertiliser application rates achieve higher expected profits (Scenario 3). When we consider farmer's risk preferences, the benefits of supplemental irrigation are enhanced because it increases average profits and reduces their volatility, driving up the CE by these two factors. Our results show that for a moderate risk aversion level (ARA equal to 0.0039), all scenarios yield positive CEs. While the baseline rain-fed scenario implies a CE of 179 $/ha, it increases as irrigation is extended to larger shares of the basin, and scenarios with low increments in fertiliser application rates yield the highest values of the CE. According to the SERF method, the most risk-efficient scenario is when supplemental irrigation is applied to the highest share of the basin and with low increments in fertiliser rates (Scenario 3 with a CE of 277 $/ha).

The comparison to the risk-neutral case allows us to assess the role of irrigation and fertiliser rates in the reduction of the volatility of uncertain profits, that is, by assessing, for each scenario, the size of the risk premium—the amount of money the agent is willing to pay to avoid the uncertainty but maintaining the same level of expected utility. As expected, the rain-fed scenario (the case with the highest volatility) has the highest RP (78 $/ha), and scenarios with larger shares of supplemental irrigation have significantly lower RPs, such as Scenario 3 with a RP equal to 54 $/ha. As lower RPs are consistent with higher CE, this scenario encompasses the highest economic benefits, consistent with the conclusions of the previous paragraph. Higher risk aversion levels reinforce these conclusions.

Environmental results indicate that scenarios representing more intensive management practices lead to poorer performance. The median concentration level of nitrates in water is 1.26 mg/L in the baseline scenario, and, as expected, it increases to 1.40 mg/L (11.11%) in Scenario 1, which encompasses the larger share of supplemental irrigation and the highest increment in fertiliser application rates. Similarly, the environmental threshold for nitrate concentration (1 mg/L) is breached 53.74% of the time in the baseline scenario. However, this proportion increases by 7.75% to 57.92% in the most input-intensive scenario. We obtain qualitatively similar results for mean and median concentration levels of phosphorus.

To measure the trade-offs between the economic benefits and water pollution for each scenario, we compute the change in the per-hectare CE relative to the baseline scenario due to a unit increase in nutrient concentration levels. In the case of nitrates, scenarios with larger areas of supplemental irrigation and low increments of fertiliser rates are the ones with higher changes in CE after the mentioned increase of the nitrates concentration levels. On the other hand, in the case of phosphorus concentration levels, scenarios with low increments of irrigated area and low increments of fertiliser rates achieve the largest increases in the CE.

The results presented here have relevant policy implications. First, the benefits of expanding supplemental irrigation could be underestimated when measured only by its effect on expected profits without accounting for risk reduction. For example, assuming moderate levels of risk aversion, these risk reductions may explain about one-fourth of the economic benefits of applying supplemental irrigation. Therefore, our results render validity to the efforts to promote greater adoption of supplemental irrigation, even in relativelly high average rainfall areas, such as the San Salvador basin in Uruquay. Furthermore, our results indicate that the expansion of farming practices along the intensive margin shows not only the expected trade-off between economic benefits and environmental performance but also that different environmental indicators (nitrate concentration and phosphorus concentration) are affected differentially because of the intensification. These are the typical challenges faced by regulating and monitoring authorities, and our results document and quantify these trade-offs and are useful in informing this decision-making process characterised by competing and opposing objectives.

Finally, we emphasise that integrated models, such as the one presented here, can be used to assess other farming practices or economic instruments that might be of interest for policy analysis. In the spirit of the latter, an avenue of future research could be the introduction of taxes or subsidies in the modelling that would internalise some of the social costs of agricultural intensification and drive changes in farmers' behaviour towards adopting better management practices. Addressing externalities by the usage of such policies could modify the relative profitability of different crop sequences. The overall impacts on land use, economic results and effectiveness of different instruments for water pollution control, can be evaluated through the use of this type of IAMs.

ACKNOWLEDGEMENTS

We thank Rafael Navas and Florencia Hastings for their valuable help.

FUNDING INFORMATION

Agencia Nacional de Investigación e Innovación (ANII), Uruguay (Fondo Sectorial Innovagro, FSA PI 2018 1 148628).

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Francisco Rosas https://orcid.org/0000-0002-1725-7588

REFERENCES

Anderson, J.R. & Dillon, J.L. (1992) Risk analysis in dryland farming systems. In: *Farming systems management series no. 2, Food and Agriculture Organization of the United Nations (FAO)*. Rome: FAO.

Apland, J., McCarl, B.A. & Miller, W.L. (1980) Risk and the demand for supplemental irrigation: a case study in the corn belt. *American Journal of Agricultural Economics*, 62(1), 142–145.

Babcock, B.A., Choi, E.K. & Feinerman, E. (1993) Risk and probability premiums for CARA utility functions. *Journal of Agricultural and Resource Economics*, 18(1), 17–24.

Baker, A. (2006) Land use and water quality. In: *Encyclopedia of hydrological sciences*. Hoboken, NJ: John Wiley & Sons, Ltd.

Burek, P., Satoh, Y., Fischer, G., Kahil, M.T., Scherzer, A., Tramberend, S. et al. (2016) *Water futures and solution-fast track initiative*. Working Paper WP-16-006, International Institute for Applied Systems Analysis, Laxenburg, Austria.

Corona, J., Doley, T., Griffiths, C., Massey, M., Moore, C., Muela, S. et al. (2020) An integrated assessment model for valuing water quality changes in the United States. *Land Economics*, 96(4), 478–492.

Dai, J., Wu, S., Han, G., Weinberg, J., Xie, X., Wu, X. et al. (2018) Water-energy nexus: a review of methods and tools for macroassessment. *Applied Energy*, 210, 393–408.

Failde, A., Peixoto, C., Estol, E. & Preve, A. (2013) Estudio sobre riego agropecuario en Uruguay. *Anuario OPYPA*, 2013, 449–465.

FAO. (2021) *World food and agriculture – statistical yearbook 2021*. Rome: FAO.

Gandelman, N. & Hernandez-Murillo, R. (2015) Risk aversion at the country level. *Federal Reserve Bank of St. Louis Review*, 97(1), 53–66.

Gassman, P.W., Reyes, M.R., Green, C.H. & Arnold, J.G. (2007) The soil and water assessment tool: historical development, applications, and future research directions. *Transactions of the ASABE*, 50(4), 1211–1250.

Griffin, R., Vogl, A., Wolny, S., Covino, S., Monroy, E., Ricci, H. et al. (2020) Including additional pollutants into an integrated assessment model for estimating nonmarket benefits from water quality. *Land Economics*, 96(4), 457–477.

Hardaker, J.B., Lien, G., Anderson, J.R. & Huirne, R.B. (2015) *Coping with risk in agriculture: applied decision analysis*. Boston, MA: CABI.

Hardaker, J.B., Richardson, J.W., Lien, G. & Schumann, K.D. (2004) Stochastic efficiency analysis with risk aversion bounds: a simplified approach. *Australian Journal of Agricultural and Resource Economics*, 48(2), 253–270.

Hastings, F., Fuentes, I., Perez-Bidegain, M., Navas, R. & Gorgoglione, A. (2020) Land-cover mapping of agricultural areas using machine learning in Google Earth Engine. In Computational science and its applications–ICCSA 2020: 20th international conference, Cagliari, Italy, July 1–4, 2020, Proceedings, Part IV 20, pages 721–736. Springer.

Hertel, T., Steinbuks, J. & Baldos, U. (2013) Competition for land in the global bioeconomy. *Agricultural Economics*, 44(s1), 129–138.

IEA. (2016) *Water energy nexus, excerpt from the world energy outlook 2016*. Paris: Organisation for Economic Cooperation and Development (OECD)/IEA. Available from: https://www.iea.org/reports/water-energy-nexus.

Keiser, D.A. & Muller, N.Z. (2017) Air and water: integrated assessment models for multiple media. *Annual Review of Resource Economics*, 9, 165–184.

Khanna, M., Swinton, S.M. & Messer, K.D. (2018) Sustaining our natural resources in the face of increasing societal demands on agriculture: directions for future research. *Applied Economic Perspectives and Policy*, 40(1), 38–59.

Kling, C.L., Arritt, R.W., Calhoun, G. & Keiser, D.A. (2017) Integrated assessment models of the food, energy, and water nexus: a review and an outline of research needs. *Annual Review of Resource Economics*, 9, 143–163.

Lee, L.Y., Ancev, T. & Vervoort, W. (2012) Evaluation of environmental policies targeting irrigated agriculture: the case of the Mooki catchment, Australia. *Agricultural Water Management*, 109, 107–116.

Liu, H., Zhang, W., Irwin, E., Kast, J., Aloysius, N., Martin, J. et al. (2020) Best management practices and nutrient reduction: an integrated economic-hydrologic model of the Western Lake Erie basin. *Land Economics*, 96(4), 510–530.

Lupi, F., Basso, B., Garnache, C., Herriges, J.A., Hyndman, D.W. & Stevenson, R.J. (2020) Linking agricultural nutrient pollution to the value of freshwater ecosystem services. *Land Economics*, 96(4), 493–509.

Mekonnen, M.M. & Hoekstra, A.Y. (2016) Four billion people facing severe water scarcity. *Science Advances*, 2(2), e1500323.

Mer, F., Vervoort, R.W. & Baethgen, W. (2020) Building trust in SWAT model scenarios through a multi-institutional approach in Uruguay. *Socio-Environmental Systems Modelling*, 2, 17892.

Miao, R. & Khanna, M. (2020) Harnessing advances in agricultural technologies to optimize resource utilization in the food-energy-water nexus. *Annual Review of Resource Economics*, 12, 65–85.

Montoya, F., Gaercía, C., Pintos, F. & Otero, A. (2017) Effects of irrigation regime on the growth and yield of irrigated soybean in temperate humid climatic conditions. *Agricultural Water Management*, 193, 30–45.

Montoya, F. & Otero, A. (2019) Is irrigating soybean profitable in Uruguay? A modeling approach. *Agronomy Journal*, 111(2), 749–763.

MVOTMA. (2017). Plan Nacional de Aguas. Available from: https://www.gub.uy/ministerio-ambiente/politicas-y-gestion/planes/plan-nacional-aguas Accessed 15 September 2021.

Neitsch, S.L., Arnold, J.G., Kiniry, J.R. & Williams, J.R. (2011) Soil and water assessment tool theoretical documentation version 2009. Technical report, Texas Water Resources Institute.

OECD. (2017) *Diffuse pollution, degraded waters: emerging policy solutions*. Paris: OECD Publishing.

Pandey, S. (1990) Risk-efficient irrigation strategies for wheat. *Agricultural Economics*, 4(1), 59–71.

Pastori, M., Udías, A., Bouraoui, F. & Bidoglio, G. (2017) A multi-objective approach to evaluate the economic and environmental impacts of alternative water and nutrient management strategies in Africa. *Journal of Environmental Informatics*, 29(1), 193–201.

Plantinga, A.J. (2015) Integrating economic land-use and biophysical models. *Annual Review of Resource Economics*, 7(1), 233–249.

Pretty, J. (2018) Intensification for redesigned and sustainable agricultural systems. *Science*, 362(6417), eaav0294.

Rabotyagov, S., Campbell, T., Jha, M., Gassman, P.W., Arnold, J., Kurkalova, L. et al. (2010) Least-cost control of agricultural nutrient contributions to the Gulf of Mexico hypoxic zone. *Ecological Applications*, 20(6), 1542–1555.

Rabotyagov, S.S., Campbell, T.D., White, M., Arnold, J.G., Atwood, J., Norfleet, M.L. et al. (2014) Cost-effective targeting of conservation investments to reduce the northern Gulf of Mexico hypoxic zone. *Proceedings of the National Academy of Sciences of the United States of America*, 111(52), 18530–18535.

Rosas, F. & Sans, M. (2023) Quantifying the value to the farmer of adopting climate change resilient technologies: evidence from the agricultural sector in Uruguay. *Mitigation and Adaptation Strategies for Global Change*, 28(5), 1–18.

Shi, P., Zhang, Y., Song, J., Li, P., Wang, Y., Zhang, X. et al. (2019) Response of nitrogen pollution in surface water to land use and socialeconomic factors in the Weihe River watershed, Northwest China. *Sustainable Cities and Society*, 50, 101658.

Williams, J.R., Jones, C.A., Kiniry, J.R. & Spanel, D.A. (1989) The EPIC crop growth model. *Transactions of ASAE*, 32(2), 497–511.

How to cite this article: Souto, A., Carriquiry, M. & Rosas, F. (2024) An integrated assessment model of the impacts of agricultural intensification: Trade-offs between economic benefits and water quality under uncertainty. *Australian Journal of Agricultural and Resource Economics*, 68, 315–334. Available from: https://doi.org/10.1111/1467-8489.12555