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Key Points:
- Socio-economic agents' decision-making is a determinant factor driving/affecting hydrologic processes
- A holistic, multifactor perspective is required to evaluate the impacts of policy interventions in complex human-water systems
- Socio-hydrologic analysis requires both innovative and integrative socio-economic and eco-hydrologic modeling frameworks

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Rationalizing Systems Analysis for the Evaluation of Adaptation Strategies in Complex Human-Water Systems

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Abstract Water resources management is a nontrivial process requiring a holistic understanding of the factors driving the dynamics of human-water systems. Policy-induced or autonomous behavioral changes in human systems may affect water and land management, which may affect water systems and feedback to human systems, further impacting water and land management. Currently, hydro-economic models lack the ability to describe such dynamics either because they do not account for the multifactor/multioutput nature of these systems and/or are not designed to operate at a river basin scale. This paper presents a flexible and replicable methodological framework for integrating a microeconomic multifactor/multioutput Positive Multi-Attribute Utility Programming (PMAUP) model with an eco-hydrologic model, the Soil and Water Assessment Tool (SWAT). The connection between the models occurs in a sequential modular approach through a common spatial unit, the "hydrologic-economic representative units" (HERUs), derived from the boundaries of decision-making entities and hydrologic responsive units. The resulting SWAT-PMAUP model aims to provide the means for exploring the dynamics between the behavior of socio-economic agents and their connection with the water system through water and land management. The integrated model is illustrated by simulating the impacts of irrigation restriction policies on the Río Mundo subbasin in south-eastern Spain. The results suggest that agents' adaptation strategies in response to the irrigation restrictions have broad economic impacts and subsequent consequences on surface and groundwater hydrology. We suggest that the integrated modeling framework can be a valuable tool to support decision-making in water resources management across a wide range of scales.

1. Introduction

Water is a fundamental resource for the functioning and sustenance of social-ecological systems, as it maintains ecological processes, regulates the climate system, and is a driver of economic growth (UN-Water, 2016). The provisioning of water resources, particularly freshwater, links the water-based ecosystem services with the demand from socio-economic systems (Millennium Ecosystem Assessment, 2005). The dynamics of water resource provisioning in social-ecological systems is not trivial, since societal, economic, and/or environmental changes can potentially alter the balance between supply and demand for water resources (Intergovernmental Panel on Climate Change, 2014). In the Anthropocene (Crutzen, 2002), the consideration of changes in water cycle dynamics and consequent management of water resources at a basin scale is no longer feasible without taking into consideration the interactions and feedback between natural and human systems (Sivapalan et al., 2012). River basins located in arid and semiarid regions are of particular concern in managing these feedback (Vörösmarty et al., 2000).

In water-scarce regions, conventional water management approaches and water policies based on increasing water provisioning for socio-economic systems is becoming both environmentally and economically unfeasible due to incremental costs of additional water resources and inelastic water supplies (Randall, 1981). As a consequence, structural scarcity and/or temporary shortages may occur, often resulting in increasing competition for water resources between natural and human systems (United Nations, 2017). Following a precautionary approach inspired by the principles of integrated water resources management and, in particular, sustainable development (International Conference on Water and the Environment, 1992), policy makers are shifting their priorities to making economic uses of water compatible with the sustainability of ecological systems. These planned adaptation actions are also supposed to enable both economic resilience against future shocks and social welfare maximization (Organisation for Economic Co-operation and Development, 2015).

Effective planned adaptation actions should, however, also take into account responses at the individual level. For example, empirical evidence suggests that farmers' perception of water scarcity, particularly in drought-prone areas, is a key factor determining autonomous adaptation behavior in agricultural systems (Alam, 2015; Rezaei et al., 2017; Udmale et al., 2014). As a result, policy-induced or autonomous behavioral changes in human systems may affect water and land management, which may affect the dynamics of hydrologic systems and generate feedback responses from agricultural systems, further impacting water and land management practices (Anderies, 2015; Palmer & Smith, 2014; Steffen et al., 2011). As a consequence, interactions between agricultural and hydrologic systems should be taken into account when designing policies in order to ensure the sustainability of social-ecological systems (Ostrom, 2009).

The realization of complex interactions within and between social-ecological systems has spurred an increasing number of decision support systems (DSS), notably quantitative models underpinned by systems analysis research, to provide quantitative information regarding the implementation of water policies (Harou et al., 2009; Heinz et al., 2007; Sood & Smakhtin, 2015). Systems analysis provides the means to assess the costs and benefits of alternative management strategies following agronomic, hydrologic, or economic criteria, or a combination thereof (i.e., hybrid approaches; Feldman, 1992; Singh, 2012). Trends in systems analysis research and DSS for water management reveal a distancing from traditional hydrologic-centered analysis and a move toward an integrative, hybrid hydro-economic approach (Bierkens, 2015; Esteve et al., 2015). Most hybrid hydro-economic models combine hydrologic and microeconomic models that represent agents' decisions on water use through piecewise exogenous equations relating water use to economic benefits (Harou et al., 2009). Accurately measuring and representing the choices that lead to the provision of the attribute or attributes that maximize utility requires the consideration of multiple inputs, such as water availability, labor, fertilizers, and machinery. Therefore, a multifactor perspective is required, enabling the measurement of marginal costs (if the objective is profit maximization) or marginal utilities (if the objective is utility maximization) of observed output levels: "an essential piece of economic information to accurately understand and predict agents' behavioral responses" (Paris, 2015). Indeed, a change in the allotment of a specific input, say water, will affect its marginal utility or shadow price, and also that of the remaining inputs, which will be reallocated so that utility is maximized in the new input availability scenario.

Significant efforts to expand hybrid hydro-economic frameworks have been made in the area of socio-hydrology. A recent study by Fraser et al. (2013) has explored the long-term dynamics of socio-economic and hydrologic systems by studying the changes in vulnerability of world's cereal crops as affected by climate change projections by coupling a global hydrological and adaptive capacity models. Fabre et al. (2015) have proposed an integrative modeling framework for the assessment of the balance between water demand and availability over long time periods and at a river basin level. A list of other socio-hydrology studies that include some aspect of modeling human-water interactions can be found in Blair and Buytaert (2016).

As of yet, no study of agricultural water reallocation and productivity offers a flexible and replicable framework that models the relevant feedback among inputs happening at a microeconomic scale in concert with a hydrologic module. Available studies "either incorporate field- and basin-level aspects but focus only on a single input (water) or, when considering a multi-factor approach, do not tackle the basin level" (Scheierling et al., 2014). Conventional hybrid hydro-economic models typically represent the behavior of water users through piecewise exogenous benefit functions for relating water use to profit. However, this approach often neglects the intrinsic complexity in economic agents' behavior and undervalues the role of human responses to policy interventions or physical shocks, potentially leading to inaccurate system robustness and resilience modeling, maladaptation, and ineffective policy design (Blair & Buytaert, 2016). The limited studies that connect full-fledged multifactor microeconomic and hydrologic models often rely on ad-hoc and/or one-way sequential coupling procedures, which are challenging to replicate and/or negate the possibility to assess feedback responses between human and water systems (Di Baldassarre et al., 2013).

This paper presents a flexible and replicable methodological framework promoting a sequential, two-way modular integration of socio-economic and eco-hydrologic models for the study of coupled complex agricultural-hydrologic systems by: (i) enabling the consideration of multiple factors capable of driving the preferences of socio-economic agents in agricultural systems; (ii) allowing the exchange of information between the socio-economic and eco-hydrologic models, and; (iii) incorporating feedback responses from one system to another. The main goal of the framework is to provide quantitative information for supporting efficient decision-making and policy-making in complex agricultural-hydrologic systems. The coupling between the socio-economic and the physical environment is provided by a common spatial element, hereinafter defined as hydrologic-economic representative units (HERUs). This flexible and replicable framework allows for the integration of full-fledged socio-economic and eco-hydrologic models.

The methods are illustrated by combining a multioutput and multifactor Positive Multi-Attribute Utility Programming (PMAUP) model (Gómez-Limón et al., 2016; Gutiérrez-Martín & Gómez, 2011) with the eco-hydrologic Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998). The PMAUP model follows a multiattribute, deductive approach capable of identifying and analyzing socio-economic agents' behavior, while SWAT is a comprehensive river basin scale model capable of simulating and assessing the relationships between the impacts from land and water management on hydrologic, biogeochemical, and ecological processes at the river basin scale. The connection between the two modeling techniques is provided by common spatial elements, the HERUs, which are entities endowed with decision-making capacity, resulting from the unique combination of hydrologic responsive units and spatially defined socio-economic agents. The combination of PMAUP and SWAT models enables the development of a spatially distributed integrative framework capable of linking socio-economic and eco-hydrologic systems, resulting in a step-forward toward the development of a socio-hydrologic instrument and, hence, underpinning the foundations for the study of the dynamics of complex human-water systems. To the best of our knowledge, this is the first time that an approach accounting for both multiple inputs and human-water dynamics at the basin level is developed and applied in a context of water policy design and water management DSS.

The capabilities of the coupled SWAT-PMAUP model are illustrated with an application to the Rio Mundo River Basin (RMRB), a subbasin of the semiarid, water-scarce, and drought-prone Segura River Basin (SRB) in south-eastern Spain, to assess human-water dynamics following the implementation of an irrigation restriction policy. In order to highlight the importance of considering the complexity of coupled human-water systems in hydro-economic simulations, the hydrologic and economic results generated by the coupled SWAT-PMAUP model are compared with the results generated by the SWAT model alone without taking into account the behavior and preferences of socio-economic agents.

2. Methods

2.1. The Microeconomic Module

Microeconomic modeling analyzes the pattern of yields, revenues, and costs of socio-economic agents as an individual (e.g., farmers) or group of individuals (e.g., representative farmers). Agents are assumed to be rational entities, making decisions on the allocation of multiple inputs in accordance to the maximization of their utility with respect to single or multiple objectives, and within a domain defined by a number of constraints. In the case of agricultural systems, the agents' decisions include crop selection and land management (e.g., fertilization), water application, and investments in capital stock. This complex decision-making problem involves multiple inputs and is often simplified by assuming each possible combination of crops and management techniques as a unique crop x_i (Graveline, 2016). This assumption allows the decision-making problem to be reduced to a choice on the crop portfolio (x) within a domain ($F(x)$), where the crop portfolio (x) is a vector representing the land share devoted to each individual crop (x_i). Mathematically, this concept can be expressed as follows:

$$x = (x_1 x_2, \dots, x_n), 0 \le x_i \le 1), \sum_{i=1}^{n} x_i = 1, \quad x \in F(x) \tag{1}$$

The agent does not have any direct preferences over the crop portfolio itself, but the crop decision-making is directly influenced by the utility the agent obtains from the crop portfolio.

Empirical microeconomic models often assume that agents are rational profit maximizers and that utility *equals* profit. However, this approach is somewhat limiting as it often does not accurately reproduce the behavior of socio-economic agents due to possible significant divergences between observed and simulated decisions (Grames et al., 2016). Alternatively, approaches such as Expected Utility (von Neumann & Morgenstern, 1953) and Positive Mathematical Programming (Howitt, 1995) assume that utility *is a function of* profit. Expected Utility is the dominant theory to model choice under risk in applied economics (Just & Peterson, 2010), while Positive Mathematical Programming is the dominant approach to calibrate agricultural programming models (Heckelei et al., 2012). However, significant empirical evidence shows that the variance in farmers' observed strategic and entrepreneurial behavior often cannot be explained by profit maximization alone (Basarir & Gillespie, 2006; Berkhout et al., 2010; Kallas et al., 2010; Solano et al., 2006).

Against this backdrop, the Theory of Planned Behavior (TPB) disputes the notion that farmers' behavior can be modeled by maximizing profits or with a utility function where profits are the single relevant attribute, and argues that farmers' observed behavior is driven by multiple (and often conflicting) attributes related to their socioeconomic, cultural, and natural situation, including but not limited to profit (Ajzen, 1991; Gassman et al., 2009; Harman et al., 1972; Harper & Eastman, 1980; Smith & Capstick, 1976). According to the TPB, observed choices are explained by farmers' attitudes toward their behavior (i.e., cropping decisions), where attitudes can be seen as "a summary of psychological evaluations based on agent's beliefs about the 'goodness' or 'badness' of an object, normally associated with a particular attribute" (Gómez-Limón et al., 2016). The implications of the TPB for farmers' behavioral modeling are that modeling farmers' behavior requires the consideration of more than one attribute.

The TPB provides the foundation for the development of a growing research body on multiattribute utility functions aiming to capture utility-relevant attributes, starting from the seminal work by Keeney and Raiffa (1993). In multiattribute utility maximization problems, rational economic agents will choose the crop portfolio x that maximizes the utility derived from the provision of valuable attributes $z(x)$ within a domain $F(x)$:

$$\underset{x}{\text{Max}\, U(x)} = U(z_1(x); z_2(x); z_3(x) \ldots z_m(x)) \tag{2}$$

$$\text{s.t.}: \quad 0 \leq x_i \leq 1 \tag{3}$$

$$\sum_{i=1}^{n} x_i = 1 \tag{4}$$

$$x \in F(x) \tag{5}$$

$$z = z(x) \in R^m \tag{6}$$

Attributes ($z(x)$) are quantifiable unit interval factors that serve as values in the agent's decision-making process. Higher attribute values indicate more desirable situations with an attribute of value equal to 1 representing an optimal situation. Assuming that it is possible to quantify relevant crop attributes (e.g., profit), alternative crop portfolios can be ranked in accordance to their resulting utility. Moreover, since the outcome of the utility function is an ordinal value, there is no risk of correlation among attributes (Edgeworth, 1881). PMAUP models focus on ranking alternative decisions that are coherent with observed choices, so that agents cultivate a crop portfolio that maximizes their utility within a domain, $x \in F(x)$, defined by a set of quantifiable constraints, including water availability, land availability, climatic and soil constraints, crop planting constraints, and crop rotations.

1. *Water availability constraint*. Water withdrawals must not exceed the water allotment set by water institutions, that is:

$$\sum_{i=1}^{n} w_i \, x_i \leq W \tag{7}$$

where w_i is the water requirement of crop x_i and W represents the total availability.

2. *Land availability constraint*. The irrigated surface area must not exceed irrigable surface area. If rainfed crops are introduced (e.g., the water allocation constraint is strengthened), agricultural land use must not exceed available agricultural surface area (see equation (1)).

3. *Climatic and soil constraints*. Each area has specific climatic and/or soil characteristics that favor certain crop varieties, meaning that irrigators' choices are typically restricted to crops that are observed in the area:

$$\sum_i y_i x_i = 0 \mid y_i \in \{0, 1\} \tag{8}$$

where a value $y_i = 0$ means the crop has not been observed in the area during the time period covered by the database and a value of $y_i = 1$ means the crop has been observed.

4. *Crop planting constraints*. This restriction sets an upper and/or lower bound to the surface area of those crops subject to a specific policy restriction.

Upper bound:

$$\varphi_i x_i \leq (1 - b_i) x_i^0 \;\middle|\; \varphi_i \in \{0, 1\}; 0 \leq b_i \leq 1 \tag{9}$$

Lower bound:

$$\varphi_i x_i \geq (1 + b_i) x_i^0 \;\middle|\; \varphi_i \in \{0, 1\}; 0 \leq b_i \leq 1 \tag{10}$$

where φ_i is a vector that activates/deactivates the restrictions for a specific crop x_i and b_i is a vector that indicates the maximum percentage the share of a crop can increase/decrease. In our study, we use crop surface restrictions to constrain changes in the area of permanent crops. Farmers can remove permanent crops, but this decision results in significant capital disinvestments, including through the disruption in the provision of carbon sequestration services. We apply a precautionary approach and set a lower and upper bound for permanent crops of ±10% in relative area change with respect to the baseline scenario which represents policies that may encourage tree conservation, such as the Common Agricultural Policy and the Spanish Drought Management Plans. This situation introduces significant uncertainty in the costs of removing trees following a hypothetical water restriction policy and complicates the estimation of an annuity that accurately represents the costs of removing a given permanent crop in the simulations.

5. *Crop rotations*. The surface area of a given crop or group of crops cannot exceed the surface area of the crop or crops they replace (Gutierrez-Martin, 2013):

$$\sum_{i,j} g_{i,j} x_i \leq \sum_{i,j} h_{i,j} x_i^0 \;\middle|\; g_{i,j} \in \{0, 1\}; \;\; h_{i,j} \in \{0, 1\} \tag{11}$$

where $g_{i,\,j}$ and $h_{i,\,j}$ are vectors whose components can adopt a value of 1 or 0 to activate or deactivate the restriction.

The calibration procedure of the PMAUP model consists of determining the parameters of the utility function (U) that make the solution to the optimization problem above (optimal crop portfolio x^*) and consistent with real-life observed decisions (x^0). The PMAUP model thus aims to generate an objective function whose solution x^* is consistent with x^0 and the choice domain $F(x)$ (Varian, 2006). Following standard microeconomic theory, the parameters of the utility function for a given finite set of attributes are elicited by equalizing the Marginal Rate of Transformation (MRT$_{kp}$), which represents the opportunity cost between two attributes z_p, z_k and is obtained as the slope of the efficient frontier β_{kp}, and the Marginal Rate of Substitution (MRS$_{kp}$), which further represents the willingness to sacrifice one unit of attribute z_p for one unit of attribute z_k:

$$\text{MRT}_{kp} = \beta_{kp} = \text{MRS}_{kp} = -\frac{\partial U / \partial z_p}{\partial U / \partial z_k}; \quad \forall p \neq k \tag{12}$$

The utility function parameters are elicited in three steps, which are explained in more detail in the next sections:

1. *Efficient frontiers* are revealed for each pair of attributes (z_p and z_k), and the tangency point for the utility function's indifference curve is obtained.

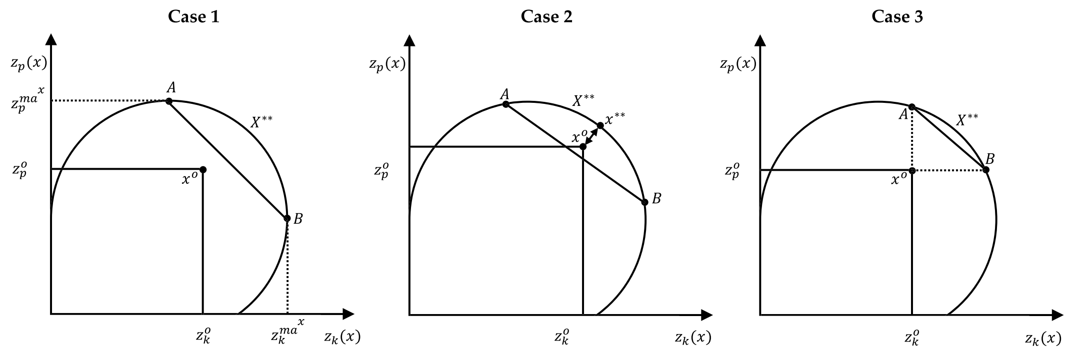

Figure 1. Procedures for projecting observed points onto linear approximations of the efficient set.

2. Given a tangency point, the *utility function* parameters are calibrated *for every possible combination of attributes* by equalizing the MRT_{kp} and the MRS_{kp}.
3. Error terms are then obtained by computing the difference between observed and simulated choices. The utility function with the lowest error is assumed to reveal the *relevant attributes*, which is the utility function that can most accurately simulate socio-economic agents' behavior.

2.1.1. Marginal Rate of Transformation

The rational agents are assumed to be efficient; that is, the agents decide what is best for them given a range of feasible options. Mathematically, the decisions must belong to the Pareto efficient set, defined as the efficient frontier. Hence, among all feasible choices, the PMAUP model reveals only those along the efficient frontier, where the indifference curve lands and where socio-economic agents maximize their utility. In a multiattribute context, the efficient frontier represents the maximum value an attribute z_p can attain given a certain value of an attribute z_k within the domain.

Constraint weighting or the multiobjective simplex method can be used to estimate points along the efficient frontier (André, 2009); yet, efficient frontiers usually cannot be analytically defined using a closed function, especially where nonlinear restrictions occur. A number of alternatives exist to estimate the efficient frontier and to reveal the "landing point" for the utility function. Amador et al. (1998), André et al. (2010), and Sumpsi et al. (1997) maximize each attribute separately within the domain to calculate the pay-off matrix (i.e., the maximum value each attribute can attain within the domain), and approximate the efficient frontier through a hyper-plane connecting two efficient points in the pay-off matrix. This methodology is illustrated by the segment formed by points A and B in in Figure 1-case 1. André and Riesgo (2007) project the observed choice to the closest efficient point x_k^{**} along the actual frontier, which is then used as a reference point to obtain a "compromise set" consisting of a set of efficient points in the vicinity. The compromise set is interpreted as the fraction of the efficient frontier where the utility function is maximized. Then the "landing area" or tangency point for the indifference curve is obtained by regressing a hyper-plane from the compromise set (segment formed by points A and B in Figure 1-case 2). Finally, Gutiérrez-Martín and Gómez (2011) obtain the maximum feasible value of attribute z_p for the observed value of z_k (z_k^o), and vice versa, again using a hyper-plane connecting the two points to approximate the efficient frontier (segment formed by points A and B in Figure 1-case 3).

Since efficient frontiers are convex (otherwise, there is no trade-off and the choice between the two attributes becomes irrelevant), the hyper-planes connecting efficient points will not belong to the actual efficient set X^{**} and will lead to approximation errors (distance between segment AB and X^{**} in Figure 1). This paper follows the method proposed by Gutiérrez-Martín and Gómez (2011) (case 3), which minimizes the approximation error for the database of the case study area (Pérez-Blanco & Gutiérrez-Martín, 2017). In case 3, the tangency point or landing area for the indifference curve is obtained solving the following optimization problems for each pair of attributes z_p and z_k within the attribute set:

$$\underset{x}{\text{Max}}\ z_p(x) \tag{13}$$

$$\text{s.t.}: z_k(x) = z_k^o(x) \quad \forall k \neq p \tag{14}$$

$$0 \le x_i \le 1 \tag{15}$$

$$\sum_{i=1}^{n} x_i = 1 \tag{16}$$

$$x \in F(x) \tag{17}$$

And:

$$\underset{x}{\text{Max}}\ z_k(x) \tag{18}$$

$$\text{s.t.}: z_p(x) = z_p^o(x) \quad \forall k \ne p \tag{19}$$

$$0 \le x_i \le 1 \tag{20}$$

$$\sum_{i=1}^{n} x_i = 1 \tag{21}$$

$$x \in F(x) \tag{22}$$

This procedure projects the observed crop portfolio $\tau_{z_p,z_k}(x^o)$ to the efficient frontier and yields two points, namely, τ_{z_p,z_k^o} and $\tau_{z_p^o,z_k}$ (points A and B in in Figure 1-case 3). The slope between the two projected efficient points in any intermediate point τ is obtained as

$$\text{MRT}_{kp}^{\tau} = \beta_{kp}^{\tau} = \frac{z_p - z_p^o}{z_k - z_k^o} \tag{23}$$

The slope between the two projected points β_{kp}^{τ} approximates the marginal opportunity cost of trading attribute z_k off for attribute z_p, or MRT, and is used as the tangency point for the calibration of the utility function.

2.1.2. Marginal Rate of Substitution

The Marginal Rate of Substitution MRS_{kp} measures the willingness to give up one unit of attribute z_k in exchange for a unit of attribute z_p, which graphically corresponds to the slope of the indifference curve (MRS_{kp} in equation (12)). Rational economic agents will choose the crop portfolio where the MRS_{kp} over the indifference curve equals the MRT_{kp} over the efficient frontier for any pair of attributes. Equating the MRT_{z_p,z_k} and MRS_{z_p,z_k} at an efficient point τ yields a system of equations from which the parameters of the objective function for every possible combination of one or more attributes are obtained:

$$\text{MRT}_{kp}^{\tau} = \beta_{kp}^{\tau} = \text{MRS}_{kp}^{\tau}; \quad \forall p \ne k \tag{24}$$

Normalizing equation (24) yields

$$\sum_{p=1}^{m} \alpha_p = 1 \tag{25}$$

Typically, several valid utility functions can be obtained. For the case of single-attribute utility functions, Varian (1982) presented a way to describe the entire set of utility functions consistent with observed preferences, while Varian (1983) obtained bounds on specific functional forms. The information provided by the MRT_{kp} and MRS_{kp} allows the elicitation of the parameters of a multiattribute utility function consistent with observed choices within the domain $F(x)$, for a given functional form. For the PMAUP model utilized in this work, it is assumed that the multiattribute utility function adopts a Cobb-Douglas specification, which offers a sensible approximation to actual farmers' behavior (Sampson, 1999). As compared to alternative additive or multiplicative-additive specifications, a Cobb-Douglas function offers the advantages of convex indifference curves and decreasing marginal utility for each attribute, thus avoiding simplistic simulations of irrigators' behavior resulting from additive utility functions with linear indifference curves and constant marginal rate of substitution (Montilla-López et al., 2018). Cobb-Douglas functions also avoid total compensability among attributes, where lower values for a given attribute can be compensated by higher values for any other attribute, irrespective of whether the former reaches unacceptable levels for the irrigator (Gómez-Limón et al., 2016). Finally, a Cobb-Douglas specification complies with the Inada conditions and guarantees the existence of a global optimum (Inada, 1963). By equalizing the MRS_{kp} of a Cobb-Douglas utility function and the MRT_{kp} obtained in the previous section, the objective function parameters can be estimated after solving the following system of equations:

$$MRS_{kp} = -\frac{\alpha_p}{\alpha_k}\frac{z_k}{z_p} = \beta^{\tau}_{kp} = MRT^{\tau}_{kp}; \quad \forall p \neq k \tag{26}$$

$$\sum_{p=1}^{m} \alpha_p = 1 \tag{27}$$

Finally, the values of the parameters obtained by resolving the system of equations above for alternative attribute combinations within the set $z(x)$ are used in equations (2)–(6) to simulate the optimal crop portfolio choice (x^*) and obtain the corresponding attribute values (z^*_p; $p = 1, \ldots, m$) and utility (U^*).

2.1.3. Relevant Attributes and Utility Function Parameters

Since rational agents choose the crop portfolio that maximizes utility, the relevant attribute set and its corresponding parameter values should minimize the distance between observed and calibrated behavior. Thus, the objective function that better represents the behavior of agents is the one minimizing the error between observed and calibrated decisions, which is obtained as

$$\min(e) = \min\left(\frac{e_x + e_\tau}{2}\right) \tag{28}$$

where e_x is the distance between the calibrated and observed crop portfolio:

$$e_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{x^o_i - x^*_i}{x^o_i}\right)^2} \tag{29}$$

and e_τ measures the distance between the calibrated and observed attributes value:

$$e_\tau = \sqrt{\frac{1}{m}\sum_{p=1}^{m}\left(\frac{z^o_p - z^*_p}{z^0_p}\right)^2} \tag{30}$$

The error remaining after calibration is also used a measure of the calibration performance.

2.2. The Eco-hydrologic Module

Hydrologic modeling is a useful instrument to support the development of water management plans by providing quantitative information regarding the water dynamics and water-related processes in a river basin (Brutsaert, 2013). Hydrologic models that are capable of simulating the interactions between water and ecosystems, such as nutrient cycling throughout a river basin, vegetation and crop growth, and the provision of ecosystem services, are referred to as eco-hydrologic models.

Eco-hydrologic models are suitable for the study of the interactions between ecological, human, and water systems, including human influences in land use (e.g., crop selection, irrigation, and tillage), the latter of particular interest in this study. Moreover, these interactions should ideally be simulated as spatially distributed processes to allow for the representation of local human influences on eco-hydrologic systems. A well-documented and extensively used eco-hydrologic model that fit those requirements is the SWAT model (Arnold et al., 1998).

SWAT is a semidistributed model operating at a river basin scale, meaning that climatic forcings (e.g., precipitation and temperature), physical variables (e.g., ground surface elevations and soil infiltration properties), and ecological variables (e.g., vegetation types, evapotranspiration, and growth rates) are distributed across the basin. River basins are divided into subbasins, and stream flows are estimated at the outlet of each subbasin. Subbasins are further subdivided into smaller units known as hydrological response units (HRUs; Neitsch et al., 2011; Winchell et al., 2007). HRUs can be understood as discrete areas within a subbasin that are composed of a unique combination of land cover (including crops and other vegetation), soil, slope, and land management. The subdivision into subbasins and HRUs enables the SWAT model to not only reflect variable impacts on the hydrologic cycle for different crops and soils, both temporally and spatially, but also impacts resulting from the implementation of specific land management practices and water-related policies (Krysanova & Arnold, 2008). While the ability to define a variety of land management practices at the HRU scale is an advantage, the SWAT model lacks a socio-economic component capable of accounting for both the reasoning describing how people manage their lands and the feedback between human and water systems. As a consequence, human actions are generally assumed to be an exogenous forcing to the natural system, which has limited relevance to the study of socio-hydrologic systems (Sivapalan et al., 2014).

2.3. Integrating Socio-economic and Eco-hydrologic Processes Into a Common Modeling Framework

Acknowledging that the integration of socio-economic and eco-hydrologic systems is fundamental for a comprehensive representation of coupled human-water systems, this study proposes a methodological framework that couples a PMAUP model with the SWAT model in a modular and sequential fashion, through cropping choices, land use management, and water withdrawals. The proposed methodological framework is graphically depicted in Figure 2 and is designed to be flexible (i.e., substitution of other socio-economic and/or eco-hydrologic models is straightforward) and replicable (i.e., application to other case study areas is straightforward), provided that both models incorporate a land module with spatially distributed elements, a fundamental requirement for the definition of HERUs. HERUs are defined as the lowest level of spatially disaggregated entities endowed with decision-making capacity, resulting from the combination of hydrologic units and socio-economic agents. Each HERU is a spatially homogeneous hydrologic-economic entity, while the term spatially homogenous refers either to the level of detail required (e.g., the necessity to describe behavioral preferences at an individual or at a group of individuals level) or to the quality of data that is available (e.g., spatial resolution of physical/hydrological data) for the hydrological-economic simulations. The explanation that follows focuses on the implementation of the proposed methodological framework for the socio-economic and eco-hydrologic models used throughout this study, that is, the PMAUP and SWAT models, while the constraints for the definition of HERUs are further described in sections 3.1 and 3.2.

In SWAT, HRUs represent the model's most basic computational unit, being defined as land areas composed of homogeneous land use, management, topographical, and soil characteristics (Neitsch et al., 2011). Similarly, in traditional PMAUP applications, the most basic computational units are identified as socio-economic agents (i.e., individuals or representative group of individuals, or, in agricultural systems, farmers or agricultural districts). Both HRUs and socio-economic agents can be spatially identified; however, HRUs and socio-economic agents usually define different spatial units, as the spatial borders that define a socio-economic agent are often the result of political and/or socio-economic processes, while HRUs are the result of physical and land management characteristics. By overlaying these two spatially identified units, it is possible to identify a new spatial element for capturing both eco-hydrologic and socio-economic processes. Hence, to apply the methodological framework depicted in Figure 2, this paper reimagines the idea of HRUs as purely physical units by proposing the incorporation of the socio-economic dimension as a determinant factor for the spatial definition of representative units in social-ecological systems (i.e., HERUs), as depicted in Figure 3.

In order to incorporate the spatially defined socio-economic agents into SWAT, a raster overlay of the socio-economic agent and land use raster maps is performed prior to the HRU analysis phase in SWAT (Winchell et al., 2013). This raster overlay operation results in unique combinations of land use/socio-economic agent codes, which are then added to the SWAT project database as unique plant codes (i.e., CPNM, in table "crops") (Arnold et al., 2012). Other plant-specific parameters (e.g., BIO_E, or radiation-use efficiency) are imported from their respective land use (e.g., maize, wheat, etc.) for the generation of the unique land use/socio-economic plant codes in the SWAT project database. Land management operations are imported from their respective socio-economic agent's crop portfolio (e.g., crops to be planted in each HERU and amount of water applied for irrigation). The utilization of specific plant codes for each unique combination of spatially identified socio-economic agent and land use type enables the identification of each HERU with its respective socio-economic agent counterpart in the PMAUP model, thus enabling the exchange of information

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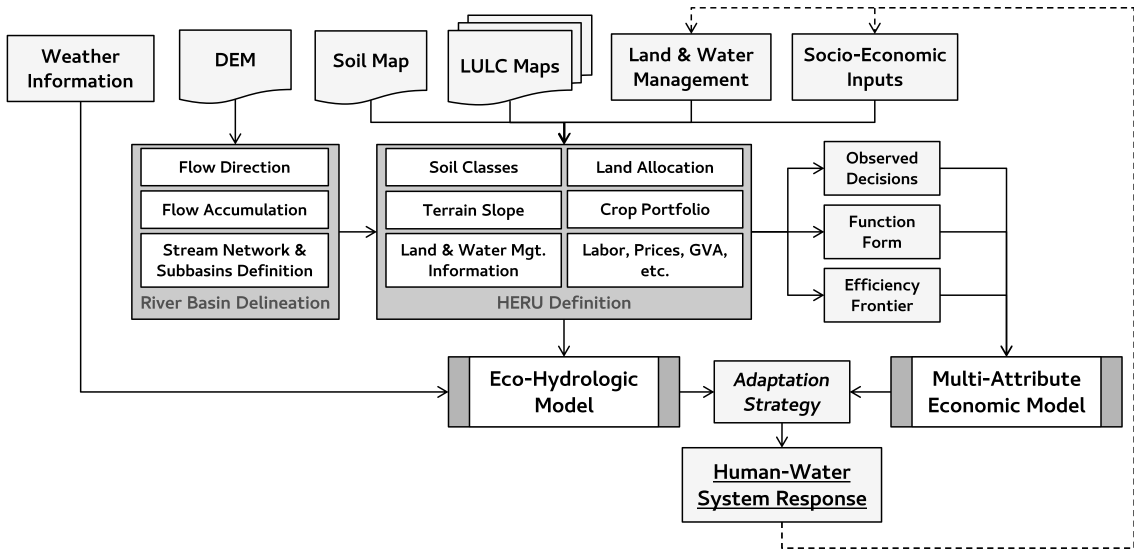

Figure 2. Modeling framework resulting from the connection between the PMAUP and the SWAT models.

between the two models. As a final step, both the final raster map (i.e., resulting from the overlay of socio-economic agents and land use maps) and the updated unique plant codes are imported to the HRU Analysis phase in SWAT as a new "Land Use map", and the definition of "HRUs" (now HERUs due to the incorporation of spatially identified socio-economic information), proceeds as in traditional SWAT applications. In areas where socio-economic agents are not present (i.e., grey areas of the Economic Agents raster layer in Figure 3), HERUs simply revert to HRUs.

Each HERU is an independent entity endowed with the capacity for decision-making. The preferences and choices identified and simulated by the PMAUP component are passed to the SWAT model as land and water management actions (Figure 2), which in this study are the crop portfolios defined in the PMAUP model (e.g., alternative crops or irrigation practices; see section 2.1). Similarly, eco-hydrologic information regarded as critical for the decision-making of economic agents is transferred from the SWAT model to the PMAUP model, which in this study is water availability for irrigation (see equation (7)). By combining physical and economic spatial information, HERUs not only enable the identification of a common spatial unit among human and water systems but also provide the means for the exchange of information between them.

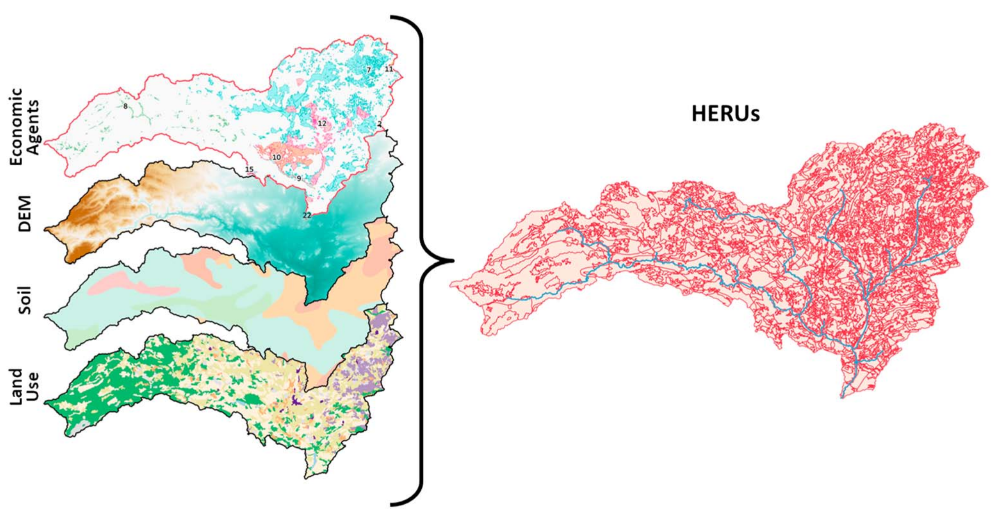

Figure 3. Schematic representation of the definition of a HERU.

Temporally, microeconomic models such as the PMAUP model run on a yearly basis (Graveline, 2016), while the SWAT model runs on a daily basis. To circumvent this temporal divergence, some considerations are made: (i) the microeconomics model simulates the preferences of farmers (i.e., crop portfolio) at the beginning of the crop season; (ii) decisions made by farmers at the beginning of a crop season are nonvariable throughout that year (Gómez-Limón et al., 2016; Gutiérrez-Martín et al., 2014); (iii) the decisions taken by farmers are passed to the hydrologic model at the beginning of the year, and parameters are updated accordingly (e.g., switch to a new crop type or reduction in the amount of water withdrawn for irrigation); and (iv) the feedback from the hydrologic to the microeconomic model are passed as an average yearly value. The yearly value is obtained by averaging the water availability from the irrigation source during the crop season at the end of every year (provided by the eco-hydrologic model), while being consistent with the way economic attributes are defined in the microeconomic model (i.e., first and second moments of a multiannual time series; see section 3.2.1).

Feedback between water and human systems are represented by the dashed line in Figure 2. The consideration of feedback between human and water systems means that changes in one system can alter the dynamics of the whole integrated modular modeling framework, a fundamental requirement for the proper representation of coupled human-water systems (Sivapalan et al., 2014). For instance, a decreased availability of water for irrigation can affect the choices of socio-economic agents in defining their crop portfolio, which, in turn, affects the crops they choose to grow, how they manage their land, and how much water they withdraw. This information is then fed back into the eco-hydrologic system by affecting fluxes, such as the evapotranspiration from the land surface and runoff to the river system and storages, including surface and groundwater storage. In the case study that follows, these connections are explored by stressing the sociological system with an irrigation restriction policy.

Similar to the way in which traditional SWAT applications simulate the eco-hydrologic processes in a river basin, the water balance is the driving force behind the hydrologic processes simulated by the eco-hydrologic component of the coupled model. The main integrating factor in the methodological framework depicted in Figure 2 is that the water balance not only drives eco-hydrological processes, such as plant growth and the movement of sediments, but also affects decisions of socio-economic agents by acting as a constraint element in the utility optimization problem, ultimately defining the farmers' crop portfolios (see section 2.1). Hence, the proposed methodological framework provides the means for revealing the preferences of people in managing the landscape, also with respect to water availability, thus contributing to the science of socio-hydrology (Sivapalan et al., 2012).

3. Implications of Water Policy in a Rational Human-Water System

3.1. Case Study Area: The Rio Mundo River Basin

The RMRB is a subbasin of the SRB in south-eastern Spain. The SRB benefits from abundant and inexpensive land and labor, adequate solar radiation, and proximity to high demand markets, resulting in one of the most productive agricultural sectors in Spain and Europe (Gómez & Pérez-Blanco, 2012). Yet water is a major limiting factor. The ratio of water withdrawals to available water resources ranges between 1.1 and 1.15 (European Environment Agency [EEA], 2016; Segura River Basin Authority [SRBA], 2015a). Approximately 86% of the 1,829 million cubic meters annually withdrawn in the SRB goes to the agricultural sector. Attempts to restore the balance in the basin have largely focused on engineering-based solutions to expand the supply base, including the construction of a diversion channel in the 1970s, the Tagus-Segura Water Transfer (TSWT), with a maximum capacity of 1,000 million cubic meters per year that imports water from the Tagus River Basin to the SRB (Figure 4a). The TSWT and other water infrastructures contributed to an increased supply base but also have created unrealistic expectations of the ability of the water system to accommodate further demand. As a result, increasing pressures on water bodies have lead the SRB into absolute scarcity. The effects of overallocation of water resources are particularly severe in downstream areas, where agriculture is more profitable, water is scarcer, and competition between economic and environmental uses has led to a widespread aquifer depletion (Avellá & García-Mollá, 2009). Reallocation from upstream agricultural uses to the environment has been suggested as a means to enhance environmental flows at the least economic cost (Martínez-Granados & Calatrava, 2014; Pérez-Blanco & Gutiérrez-Martín, 2017). Yet the economic and environmental repercussions of such intervention have yet to be assessed in an integrated socio-hydrologic framework.

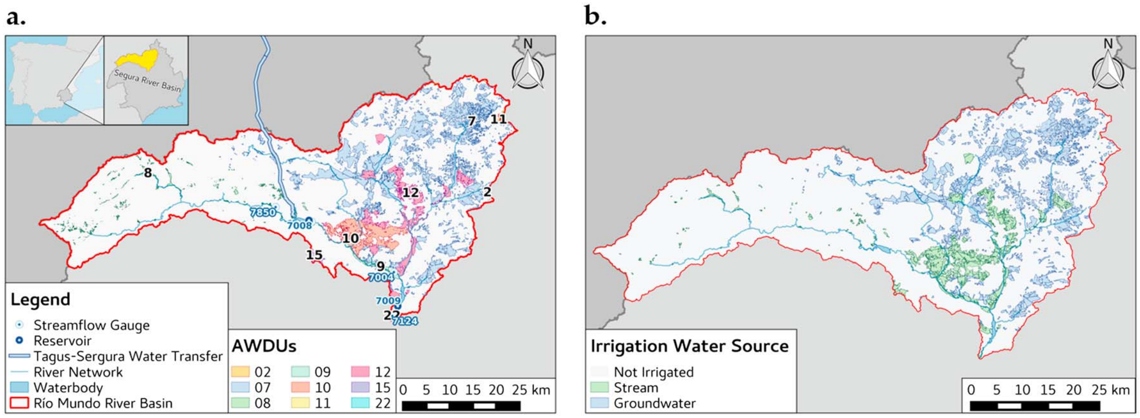

Figure 4. The case study area. (a) The Rio Mundo river basin (RMRB) and its AWDUs. (b) The spatial distribution of the main water sources for irrigation in the RMRB.

The RMRB is located upstream in the SRB and covers an area of 2,500 km^2, accounting for 15% of the SRB's total surface. The fractions of the RMRB dedicated to irrigation are categorized as Agricultural Water Demand Units (AWDUs). AWDUs are spatially defined groups of local irrigation communities sharing a common territory, water source, and hydrological and administrative characteristics (SRBA, 2014). In the RMRB, AWDUs offer the lowest spatial disaggregation level with comprehensive and readily available socio-economic data, hence being considered as the decision-making socio-economic agents in this case study. The process of aggregating individual farmers into groups to represent economic agents is well documented in the literature (Gómez-Limón et al., 2016; Gutiérrez-Martín et al., 2014), also through the use of AWDUs (Martínez-Granados & Calatrava, 2014; Pérez-Blanco & Gutiérrez-Martín, 2017). AWDUs may be composed of one or more HERUs, depending on soil, land use, and topographic characteristics of the spatial area the AWDU covers. The decision-making process of AWDUs does not directly take into account soil or topographic characteristics; however, since these spatial characteristics influence the amount of water available for irrigation, they implicitly provide information that is directly taken into consideration by the PMAUP model in determining the choices of socio-economic agents. In total, nine AWDUs are located within the RMRB area, covering a total surface land area of 425 km^2 and corresponding to 17% of the RMRB total area. Approximately 70% of the water withdrawals from AWDUs in the RMRB are from groundwater sources; particularly in the northern upper section of the RMRB (e.g., AWDU 7). Figure 4a depicts the spatial location of the AWDUs in the RMRB, while Figure 4b presents the spatial distribution of the main water sources for irrigation systems in the AWDUs.

3.2. Model Calibration

3.2.1. The Microeconomic Module

This study relies on the most comprehensive set of attributes based on previous versions of the PMAUP model, which includes: (i) profit (z_1), obtained as the expected gross margin; (ii) risk avoidance, obtained as the difference between the standard deviation of the profit maximizing crop portfolio ($\overline{\sigma}$) and that of an alternative crop portfolio x ($\sigma(\pi(x))$); and (iii) management complexity (z_3). Of the three variables considered to measure management complexity avoidance (total labor avoidance, hired labor avoidance, and direct costs avoidance), hired labor avoidance was found the best *proxy* (the other two were found nonrelevant). These attributes are described below:

$$z_1(x) = \Sigma_i x_i \pi_i \tag{31}$$

where π_i is the expected gross margin per hectare of crop i.

$$z_2(x) = \overline{\sigma} - \sigma(\pi(x)) \tag{32}$$

where $\sigma(\pi(x)) = x^t \cdot \mathrm{VCV}(\pi(x)) \cdot x$ and $\mathrm{VCV}(\pi(x))$ are the variance and covariance matrix of the per hectare crop profits ($\pi(x)$) of the crop decision x, respectively.

$$z_3(x) = \overline{\mathrm{H}} - H(x) \tag{33}$$

Table 1
PMAUP Model Inputs and Related Data Providers

ID	Data provider	Description	Ref. year/period	Disaggregation	Relevant model input
Water withdrawals and allotment	Segura River Basin Authority - SRBA (2014)	Water withdrawals and allotment for every source, including surface, groundwater, desalination, treated wastewater, and water transfer for each AWDU	2013	AWDU	W
Water application and irrigation technology	SRBA (2014)	Water application per crop and irrigation technology for each AWDU	2013	AWDU	w_i
Crop portfolio	Región de Murcia (2015), SRBA (2015b, 2014)	Crop information at municipality (hectares per crop) and AWDU levels (hectares per crop category)	2013	Municipality, AWDU	x_i^0, y_i, $g_{i,j}$, $h_{i,j}$, φ_i
Crop yields and prices	Ministry of Agriculture and Environment - MAGRAMA (2015a)	Crop yields and prices	2003–2013	Province (NUTS3)	π_i
Other revenues	MAGRAMA (2015b)	Subsidies, insurance payments, and other revenues	2003–2013	Province (NUTS3)	π_i
Costs	MAGRAMA (2015b)	Working days, variable costs, and other costs	2003–2013	Province (NUTS3)	π_i, H_i

where $H(x) = \sum_i x_i H_i$ is the hired labor requirements per hectare to produce the crop portfolio x (H_i is the hired labor requirement per hectare of crop i) and $\overline{H}$ is the hired labor requirement per hectare to produce the profit maximizing crop portfolio. Table 1 summarizes the data source and reference year of the input data used to quantify attributes in the AWDUs.

Even after minimizing the distance between observed and calibrated decisions, errors will still exist. The data set available is incomplete and limits the capacity of the PMAUP model to accurately represent crops, management techniques, relevant attributes, and binding constraints in the framework (Gutiérrez-Martín & Gómez, 2011). For example, due to insufficient observations (e.g., to obtain the expected income of olive groves under deficit irrigation), some feasible crops and/or management techniques will not be considered in the model. Some attributes may not be measurable either. For example, the TPB highlights the relevance of “subjective norms,” defined as “aggregates of the beliefs of approval/disapproval of the behavior by important individuals or groups,” in explaining agents’ behavior (Schlüter et al., 2017); yet, there is no data available to measure such variable, or a reliable *proxy* variable, in the case study area. According to Gómez-Limón et al. (2016) and Gutiérrez-Martín and Gómez (2011), reducing the calibration error necessitates a more precise delineation of the model constraints and the inclusion of additional relevant attributes. Note again that the outcome of the utility function is an ordinal value (Edgeworth, 1881); that is, the model is not concerned about total utility or levels of utility (which would cause correlation problems), but rather about ranking alternative decisions coherent with observed choices (i.e., error minimization).

The available data set covers 37 irrigated crops and 13 rainfed crops (reserve option) over the 2003–2013 period, representing 89% of the total surface area covered by the AWDUs in the case study area. All monetary values are adjusted to constant values of the calibration year, 2013. All attributes are quantities of dimension one, that is, normalized dividing by the maximum feasible value. As compared to previous versions of the model (Pérez-Blanco & Gutiérrez-Martín, 2017), the coding has been updated to normalize attributes using the maximum feasible values from the payoff matrix instead of the observed value, which could potentially lead to values higher than one. The new coding has further reduced the computational requirements in the calibration procedure by optimizing the code and removing 2000+ code lines to reduce the computational cost of the coupled model. The objective function of each AWDU is calibrated using the optimization algorithm Conopt 3 (ARKI Consulting and Development) in the General Algebraic Modeling System software (GAMS v21.4). The calibration results are shown in Table 2.

The parameters α_1, α_2, and α_3 are the values of the objective function parameters for the attributes profit (z_1), risk avoidance (z_2), and management complexity avoidance measured through hired labor avoidance (z_3). The parameters e_x and e_τ are the errors measuring the distance between observed and optimum crop

Table 2
PMAUP Model: Calibration Results

AWDU	α_1	α_2	α_3	e_x (%)	e_τ (%)	e (%)
2	0.88	0.12	0.00	2.26	8.35	5.30
7	0.78	0.22	0.00	5.27	5.91	5.59
8	0.50	0.48	0.02	7.78	5.62	6.70
9	0.85	0.04	0.11	1.38	6.22	3.80
10	0.92	0.08	0.00	3.69	3.49	3.59
12	0.80	0.20	0.00	4.07	9.07	6.57
15	0.72	0.28	0.00	1.53	3.81	2.67
22	0.83	0.17	0.00	2.26	2.12	2.19

portfolios and the distance between observed and optimum attributes, respectively, and e is the average calibration residual. The calibrated objective functions describe the agents' preferences and can serve to project behavior, provided calibration errors are low. The results in Table 2 for the performance metrics display overall a satisfactory performance with low calibration errors (average calibration residual, e, below 10%; Gómez-Limón et al., 2016).

The calibration results show that agents' decisions are largely driven by profit, while risk aversion also has a relevant role in explaining the behavior of agents. The avoidance of management complexities is considered in the decision-making process by only two AWDUs. When interpreting the results, it is important to acknowledge that the utility function parameters are not absolute values, since choices are constrained by the domain. For example, agents with a high α_1 value where the domain restricts profitable crop portfolios may display lower expected income than others with a lower α_1 value and less constraining domain.

3.2.2. The Eco-hydrologic Module

The basic information required to set up the SWAT model includes: (i) climatic data; (ii) topographic data (i.e., digital elevation model); (iii) soil spatial distribution and properties, and; (iv) land use spatial distribution and land management practices. Besides this basic information, specific information can be added in order to describe specific processes (e.g., point-source nutrient discharges) or for calibration purposes (e.g., measured streamflow data). Table 3 summarizes the data source and reference year of all the available input data used for the set-up and calibration of the SWAT model.

Spatial information pertaining to the identification of the AWDUs is also utilized during the set-up of the SWAT model, as shown in Figure 3 (SRBA, 2015b, 2014). In order to spatially connect the socio-economic information (i.e., crop portfolio in Table 1) with the eco-hydrologic information (i.e., land cover in Table 3), two considerations are made: (i) the PMAUP model treats crops that have more than one management scheme (e.g., rainfed and irrigated) as essentially different crop varieties (i.e., different options in the crop portfolio of socio-economic agents; see section 2.1); in SWAT, however, crops are assumed to be of the same

Table 3
SWAT Model Inputs and Related Data Providers

ID	Data provider	Description	Ref. year
Digital elevation model	Instituto Geográfico Nacional de España (IGN, 2017)	Digital elevation model for the Segura River Basin (25 × 25 m resolution)	2012
Soil map	European Soil Database (The European Soil Bureau, 2004)	Soil geographical database for Europe (SGDBE) v2.0 (scale 1:1,000,000)	2004
Land cover	Instituto Geográfico Nacional de España (IGN, 2017)	SIOSE CLC Corine Land Cover for Spain (scale 1:100.000)	2012
Climatic data	SWAT Global Weather Data (Fuka et al., 2014)	Daily meteorological data for the Segura River Basin area	1979–2014
Hydrologic units	Confederación Hidrográfica del Segura (SRBA-IDE, 2016)	Segura River Basin hydrologic units (e.g., river basin and subbasins delineation)	2016
Hydrologic network	Confederación Hidrográfica del Segura (SRBA-IDE, 2016)	Segura River Basin hydrologic network (e.g., stream network) in.shp	2016
Streamflow, reservoir, and channel data	Centro de Estudios Y Experimentación de Obras Públicas (CEDEX, 2016)	Daily measured streamflow, reservoir outflow, and stream flow data	1968–2014

Table 4
Calibration and Validation Results for the SWAT Model

	Calibration		Validation	
Station	NSE	PBIAS	NSE	PBIAS
7850	0.67	13.10	0.21	27.74
7003[a]	0.87	5.19	n.a.	n.a.
7004	0.80	18.44	0.67	8.21
7124	0.60	22.44	0.53	7.66

[a]Data for station 7003 were not available for the validation period.

land cover type but with different land management schemes (i.e., same crop variety but managed under a different scheme), and; (ii) unique crop varieties that share similar characteristics are aggregated into general crop classes (e.g., vineyards for grape, dry-grape, and wine production are considered simply as vineyards). Hence, the eco-hydrologic model considers a total of 21 land use classes, 14 out of which are specific, nonaggregated crop types; 11 soil classes; and nine spatially defined socio-economic agents (i.e., AWDUs), producing a final number of 806 HERUs for 31 subbasins. In order to maintain the spatial integrity with the digital elevation model, the land-cover, soil, and spatially defined socio-economic agents' maps are converted to raster format at a resolution of 25 × 25 m. HERUs were created following the methodology described in section 2.3 and depicted in Figure 2. The creation of the HERUs for this case study was supported by the ArcSWAT ArcGIS plugin (Winchell et al., 2007), where a land use map is created by crossing land use and socio-economic information, followed by crossing the topographical, soil, and land use input raster maps (the usual HRU definition steps).

Streamflow data covering the period from 1994 to 2010 was used for calibration of the SWAT model, while validation was performed using streamflow data ranging from 2011 to 2013. Four distinct streamflow measurement stations (i.e., 7003, 7004, 7124, and 7850; see Figure 4a) were used to calibrate the SWAT model. The SWAT-CUP software and the Sequential Uncertainty Fitting procedure (SUFI2; Abbaspour et al., 2007) were used for the calibration, resulting in a Nash-Sutcliffe (NSE) ranging from 0.60 to 0.87 and Percent Bias (PBIAS) ranging from 5.19 to 22.44, while validation resulted in a NSE ranging from 0.21 to 0.67 and PBIAS ranging from 7.66 to 27.74, all under a monthly scale. Calibration and validation results for the SWAT model are summarized in Table 4.

Both the NSE and PBIAS results are acceptable at a basin scale (i.e., station 7124; Moriasi et al., 2007). The poorer performance at the upstream stations is likely due to the use of the SWAT Global Weather Data (Climate Forecast System Reanalysis data set; Fuka et al., 2014), due to insufficient meteorological data from local stations at the subbasin scale.

3.3. Responses of Human-Water Systems

The case study explored as an example in this paper consists of evaluating the social-ecological consequences in the RMRB following the implementation of an irrigation restriction policy. The policy enforces the reduction of water used for irrigation with respect to an initial baseline scenario in 2013. Ten different policy scenarios are evaluated, each consisting of unique irrigation restriction values ranging from 5% (scenario p5) to 50% (scenario p50) restriction at 5% intervals. These irrigation reduction policies have been designed following similar reallocation policies that have been explored by the Segura River Basin Authority in the past, and are meant to correspond to the conservation of water to generate environmental benefits downstream. Some considerations must be highlighted:

1. Only annual crops are affected by the irrigation reduction policy; permanent crops are assumed to be not affected by the policy, thus receiving a guaranteed water supply. This is done to prevent disinvestments potentially leading to significant disruptions in ecosystem services not accounted for in the model (e.g., carbon sequestration) and is in compliance with the SRB's Drought Management Plan (SRBA, 2008). Consequently, HERUs covered with permanent crops are constrained to adapt their crop portfolio in the range of ±10% in relative area change with respect to the baseline scenario, as discussed in section 2.1.
2. The management of hydraulic infrastructures (i.e., TSWT and reservoir outflows) in the RMRB is unchanged with respect to the baseline scenario, respecting physical constraints (e.g., maximum reservoir capacity is a constraint on reservoir storage).
3. Since the AWDUs represent the socio-economic agents in the case study area, irrigation water reductions are enforced at an AWDU scale. This means that in AWDUs composed of several HERUs, a HERU inside a given AWDU may reduce water use by a higher or lower proportion than their neighbors (i.e., other HERUs inside the same AWDU) according to their preferences, as long as the overall irrigation water reduction for that particular AWDU is achieved at the AWDU scale.

Table 5
Variation in the Crop Portfolio of Farmers (Annual Crops Only) as a Response to the Implementation of an Irrigation Restriction Policy

	Area (km^2)										
Crop	Baseline	p5	p10	p15	p20	p25	p30	p35	p40	p45	p50
Alfalfa	3.72	3.72	3.70	3.73	3.77	3.87	3.94	3.76	3.15	1.33	0.83
Barley	38.54	40.15	43.46	46.87	50.44	35.28	49.66	63.01	77.22	91.50	110.89
Maize	144.99	127.13	107.78	87.51	67.13	56.84	42.87	30.48	19.30	8.80	1.57
Lettuce	0.76	0.76	0.76	0.76	0.77	0.78	0.95	1.56	2.10	1.95	2.46
Oats	10.08	10.13	10.23	10.67	11.14	12.32	11.59	11.67	11.90	13.04	13.37
Wheat	23.90	38.61	53.46	68.57	83.80	95.26	95.63	95.92	96.16	96.36	88.75
Tomato	11.01	11.08	11.17	11.24	11.34	11.66	11.87	10.75	10.31	10.40	9.07
Pepper	5.27	5.32	5.25	5.24	5.06	4.92	4.47	4.38	4.18	4.19	5.04

4. Direct reductions of water withdrawals for irrigation are passed to the eco-hydrologic model in the form of timing (i.e., amount of days between irrigation applications) and magnitude (i.e., amount of water applied per irrigation application), while indirect reductions may occur due to varying crop choices (e.g., switching from a water intensive crop to a crop with lower water requirements).

3.3.1. Human System Responses

Table 5 shows how the portfolio of the most economically relevant irrigated annual crops adjusts to the changing water constraint in the RMRB. Economic agents (i.e., AWDUs) respond to the increasingly stringent water allocation constraint by reallocating their crop portfolio x (the decision variable) in order to maximize the utility function U within the domain $F(x)$. This reallocation involves either substituting irrigated crops in the margin (i.e., those delivering lower utility levels) with less water demanding crops or rainfed crops or changing the way irrigated crops are managed, such as employing managed deficit irrigation techniques, in such a way to minimize the utility loss as compared to the baseline.

Table 5 indicates that irrigated crops are generally replaced by rainfed crops, such as barley and wheat. In some simulations, the objective function cannot be resolved within the domain due to the threshold irrigation requirements for perennial shrub and tree crops. This occurs in AWDU 2, where water allocation is reduced by ≥45%; AWDU 15, where water allocation is reduced by ≥35%; and AWDU 22, where water allocation is reduced by ≥30%. From these threshold reductions upward, no further water restrictions are applied and thus the crop portfolio remains constant.

As the water constraint is strengthened, agents tend to sacrifice the growing of more water intensive (and, in general, more valuable) crops in favor of less water intensive (and, in general, less valuable) crops. As a consequence, utility losses occur. Comparable water allocation constraints may yield asymmetric impacts on AWDUs' utility values, which is conditional on agents' preferences (as revealed in the utility function) and domain, resulting in some AWDUs suffering higher utility losses than others. The reduction in utility is accompanied by a reduction in income, measured as gross value added (GVA) and displayed in Figure 5 for each AWDU.

Overall, the AWDUs in the upstream areas of the RMRB (e.g., AWDUs 2 and 7) display less profitable crop portfolios and show lower absolute income losses as a consequence of water use restrictions with respect to downstream AWDUs (e.g., AWDUs 10 and 22). These spatial variations in GVA are important because while focusing irrigation restrictions on upstream areas may improve environmental flows along the SRB at the least cost, it also raises significant equity issues that call for some compensation to balance asymmetric on-farm losses and induced effects on the wider economy (e.g., agri-food industry; Pérez-Blanco et al., 2016).

3.3.2. Water System Responses

The implementation of an irrigation restriction policy has implications not only for the economic system within a river basin but also for the dynamics of the water system. As described in section 2.2, reduction in the amount of irrigation water application directly impacts a river basin's water balance by altering several hydrologic processes, such as evapotranspiration and percolation. Indirectly, farmers' choices regarding their crop portfolio following the implementation of a particular irrigation restriction policy are another factor capable of affecting hydrologic processes, such as the fraction of rainfall converted to runoff. Ultimately, the implementation of an irrigation restriction policy is expected to reduce irrigation return flows and alter the total amount of water leaving land areas and being converted to river flow. Figure 6 presents the main

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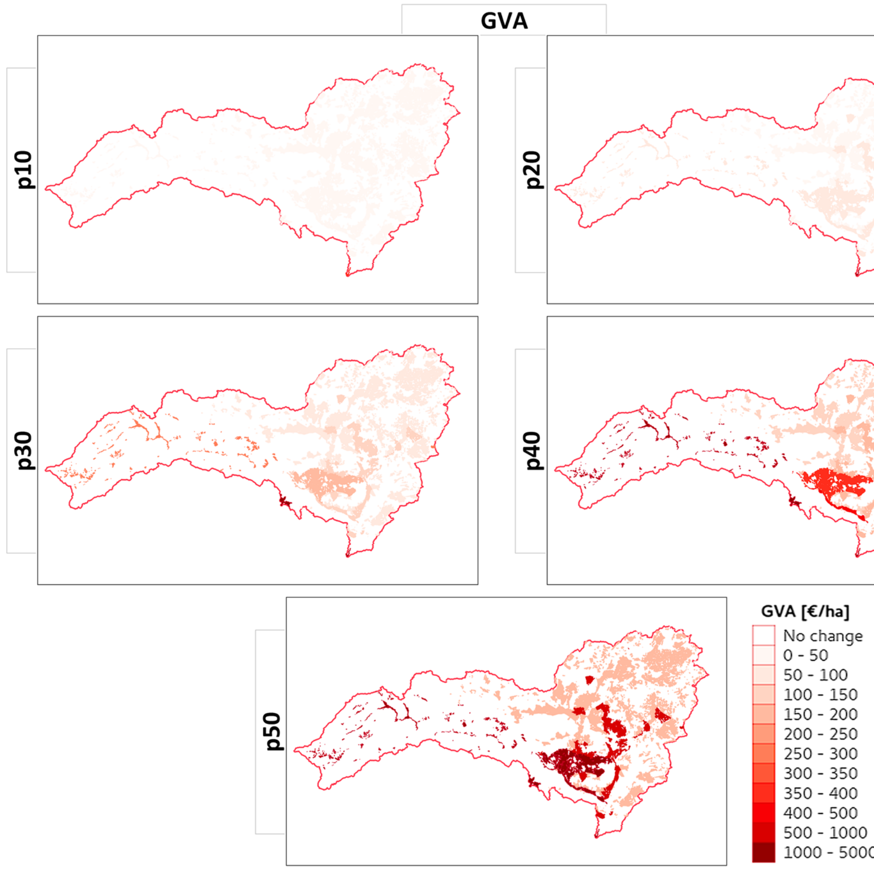

Figure 5. Foregone income-gross value added (GVA) losses per AWDU in the RMRB (€/ha).

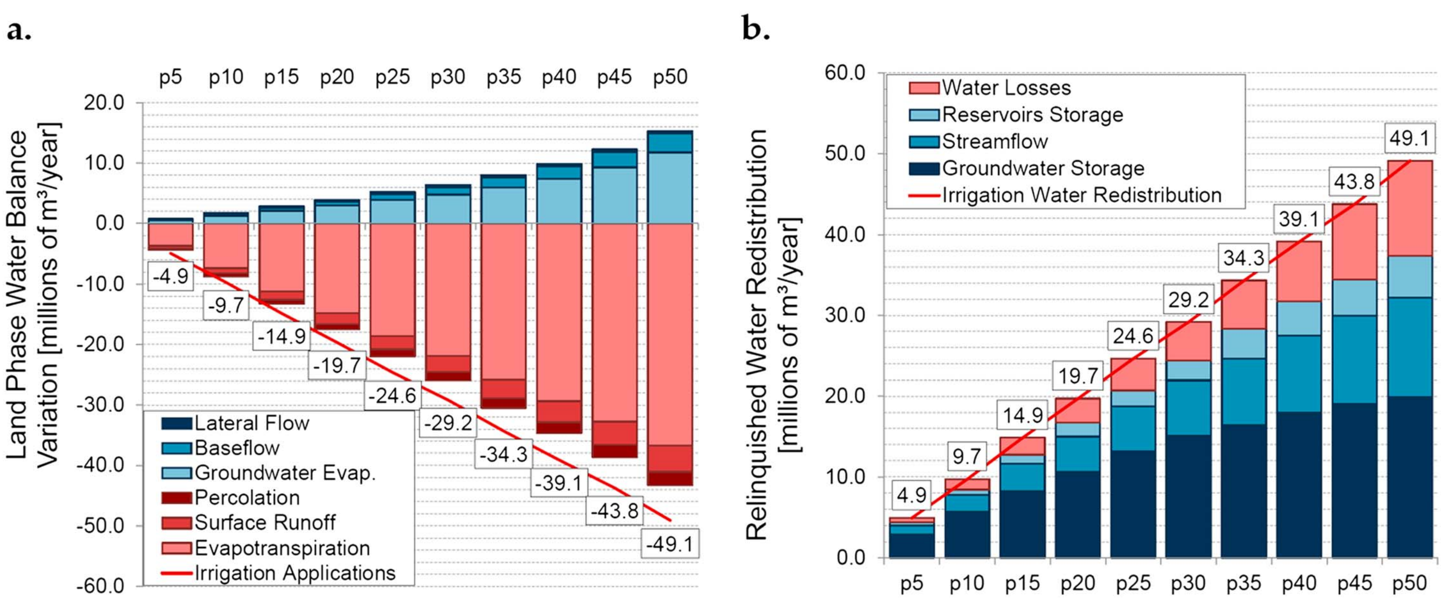

Figure 6. (a) Changes in the hydrologic balance of the RMRB after the implementation of an irrigation restriction policy. (b) Estimated redistribution of relinquished water following the implementation of an irrigation restriction policy. Values represent the absolute difference with respect to the baseline scenario.

changes in the water balance (Figure 6a) and the estimated redistribution of the relinquished water (Figure 6b) with respect to the baseline scenario after the implementation of an irrigation restriction policy in the RMRB.

In efficient irrigation systems, water that is applied to the soil during an irrigation operation is expected to be converted to evapotranspiration with minimal losses. Hence, it is not a surprise that evapotranspiration is the primary hydrologic flux affected by the implementation of an irrigation restriction policy, as shown in Figure 6a. However, not all the amount of irrigation water reduction is fully converted to evapotranspiration. Due to inefficiencies in the irrigation systems or to the natural movement of water in the soil profile, other processes of the hydrologic cycle may be affected as well, such as surface runoff and percolation past the bottom of the soil profile (Figure 6a).

In contrast, other natural processes may be affected by the reduction of irrigation applications, in particular groundwater evapotranspiration (Figure 6a). As near-surface soils become drier due to higher near-surface evapotranspiration, more water from the underlying groundwater table is transported upwards to the near surface soils. Groundwater evapotranspiration, hence, acts as a natural attenuator to the negative effects on water requirements by crops following the reduction in the amount of water applied for irrigation. However, groundwater evapotranspiration also has an impact in reducing groundwater storage.

Interestingly, Figure 6a also depicts a general slight increase in baseflow as irrigation applications are reduced at the river basin scale. As depicted in Figure 4b, the majority of the irrigated area of the RMRB utilizes groundwater as its water source for irrigation (approximately 70%). In subbasins where groundwater-fed irrigation is predominant, when irrigation applications are reduced, baseflow generally increases due to the reduced depletion of the aquifer system, even though aquifer recharge decreases (percolation in Figure 6a). In subbasins where the source for irrigation is predominantly surface waters, both aquifer recharge and baseflow processes decrease, potentially further impacting groundwater systems.

Figure 6b depicts the estimated amount of water that can be redistributed and their destinations following the implementation of an irrigation restriction policy. The water losses as expressed in this figure represent the difference between the amount of redistributed relinquished water following the implementation of an irrigation restriction policy and the amount of water that remains in the river basin system, either stored in reservoirs or groundwater systems or converted as downstream flow. From the results depicted in Figure 6a, water losses are mainly attributed to increased groundwater evapotranspiration.

In general, the destination of relinquished water following the implementation of the assessed policy depends on the source of water used for irrigation (see Figure 4b for reference). In subbasins where groundwater-fed irrigation is predominant, the majority of relinquished water remains in the aquifer system, discounting losses such as groundwater evapotranspiration. The relinquished water from subbasins where streamflow is the predominant water source for irrigation is mainly redistributed to downstream flow or artificial reservoirs storage. Water losses, however, can occur, such as evaporation from the surface of streams and reservoirs, percolation past the bottom of the reservoirs, and/or the upward movement of water from the saturated to the unsaturated zones in the soil. On average, Figure 6b shows that approximately 50% of total relinquished water in the RMRB is redistributed to groundwater, 25% to downstream flow, and 10% reservoir storage, while the remaining 15% is estimated to be lost from the system.

Spatially, the changes in water fluxes and storage are not homogeneous. Decisions taken by socio-economic agents can affect hydrologic processes in their own properties as well as in their neighbors' lands. The results in Figure 7 show that farmers' decisions at the HERU level have impacts on hydrologic fluxes at three spatial scales: (i) evapotranspiration at the local scale; (ii) groundwater evapotranspiration at the subbasin scale, and; (iii) surface water yield at a combination of local and subbasin scales. Water yield is defined as the net amount of water that contributes to streamflow in a river reach (Arnold et al., 2012).

As shown in Figure 7, the evapotranspiration is lower with respect to the baseline scenario in areas affected by the irrigation restriction policy. As less water is made available for irrigation, farmers change their crop portfolio and/or land management preferences as an adaptation measure to circumvent the negative impacts from lower availability of water. As a consequence, less water is removed from the soil profile and converted to evapotranspiration. In contrast, in areas that are not directly affected by the policy, no significant change is observable in evapotranspiration.

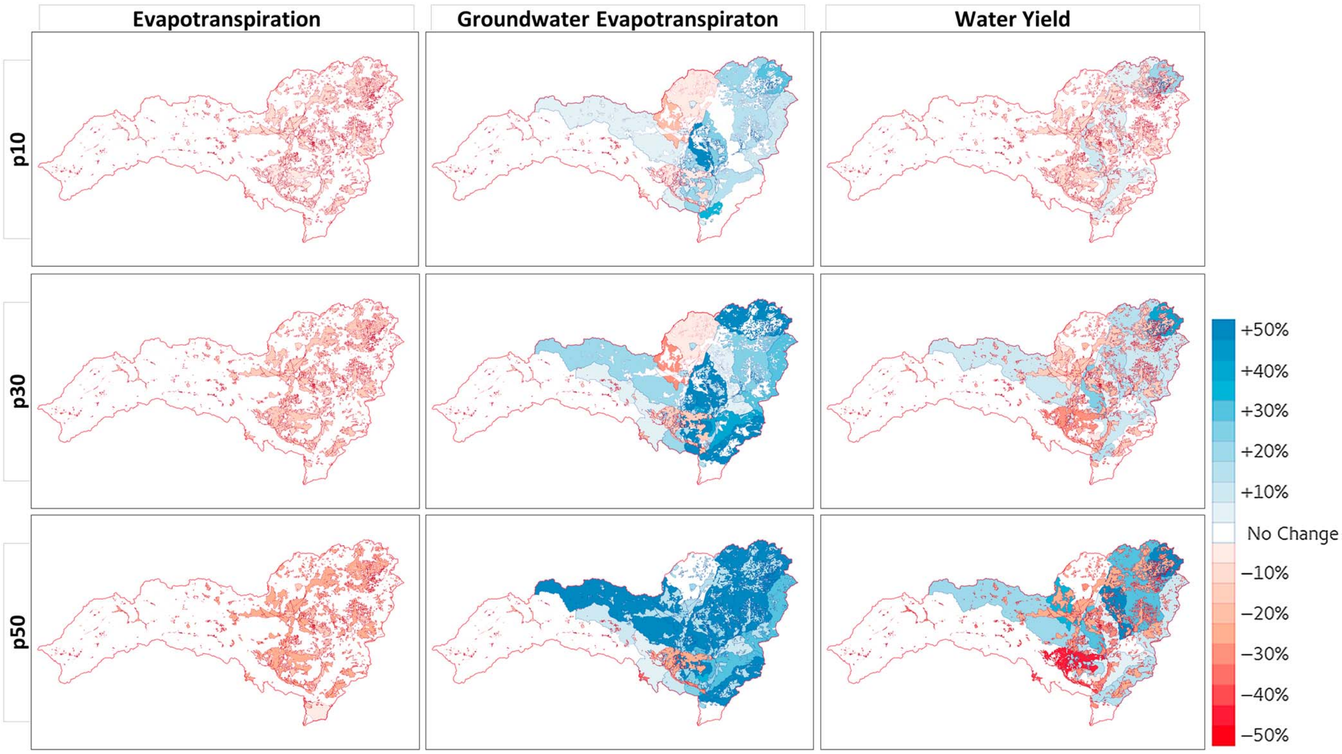

Figure 7. Relative estimated spatial variation of evapotranspiration, groundwater evapotranspiration, and water yield processes for the irrigation policy restriction scenarios of 10%, 30%, and 50% with respect to the baseline scenario.

Evaporation from groundwater can substantially impact groundwater dynamics by reducing groundwater elevations. Conversely, changes in groundwater dynamics can affect the groundwater evapotranspiration flux. Groundwater dynamics, in turn, are typically much less localized than surface processes. As a result, the socio-economic agents' choices of responses to the implementation of an irrigation restriction policy can affect the rate of withdrawals from and recharge of aquifer systems, ultimately affecting the groundwater evapotranspiration flux at a subbasin scale. Figure 7 shows that a general intensification of groundwater evapotranspiration occurs as a consequence of less water added to the soil by irrigation, especially in areas where irrigation water source is predominantly groundwater (see Figure 4b for reference).

Finally, the water yield is shown in the third column of Figure 7. Generally, AWDUs show a reduction of water yield, mainly due to the reduction of surface runoff as a consequence of reduced irrigation (i.e., irrigation return flow). In AWDUs where the water source for irrigation is mainly groundwater (e.g., northern RMRB), the reduction in water yield is less intensive than in AWDUs located in areas where the main source for irrigation is surface water (e.g., southern RMRB). In subbasins where irrigation water source is mainly groundwater, reduced withdrawals from aquifer systems result in an intensification of groundwater hydrologic processes, such as baseflow and groundwater evapotranspiration. In contrast, in subbasins where irrigation water source is mainly surface water, a general reduction in percolation and recharge of the aquifer systems occurs, having a negative impact on groundwater hydrologic processes such as baseflow and groundwater evapotranspiration.

3.3.3. SWAT-PMAUP Versus SWAT: Differences in Describing Complex Agricultural-Hydrological Systems

In order to verify if the preferences of socio-economic agents affect both hydrologic and economic processes in complex coupled human-water systems, a new set of results is generated by eliminating the ability of socio-economic agents to make reasonable decisions. Since this new scenario does not endow the socio-economic agents with decision-making capacity, they are unable to "perceive" environmental and/or socio-economic changes and to adapt accordingly. The comparison between the two scenarios (i.e., adaptive, when agents are endowed with decision-making capacity, and nonadaptive, when agents are deprived of decision-making capacity) is shown schematically in Figure 8 for selected crops.

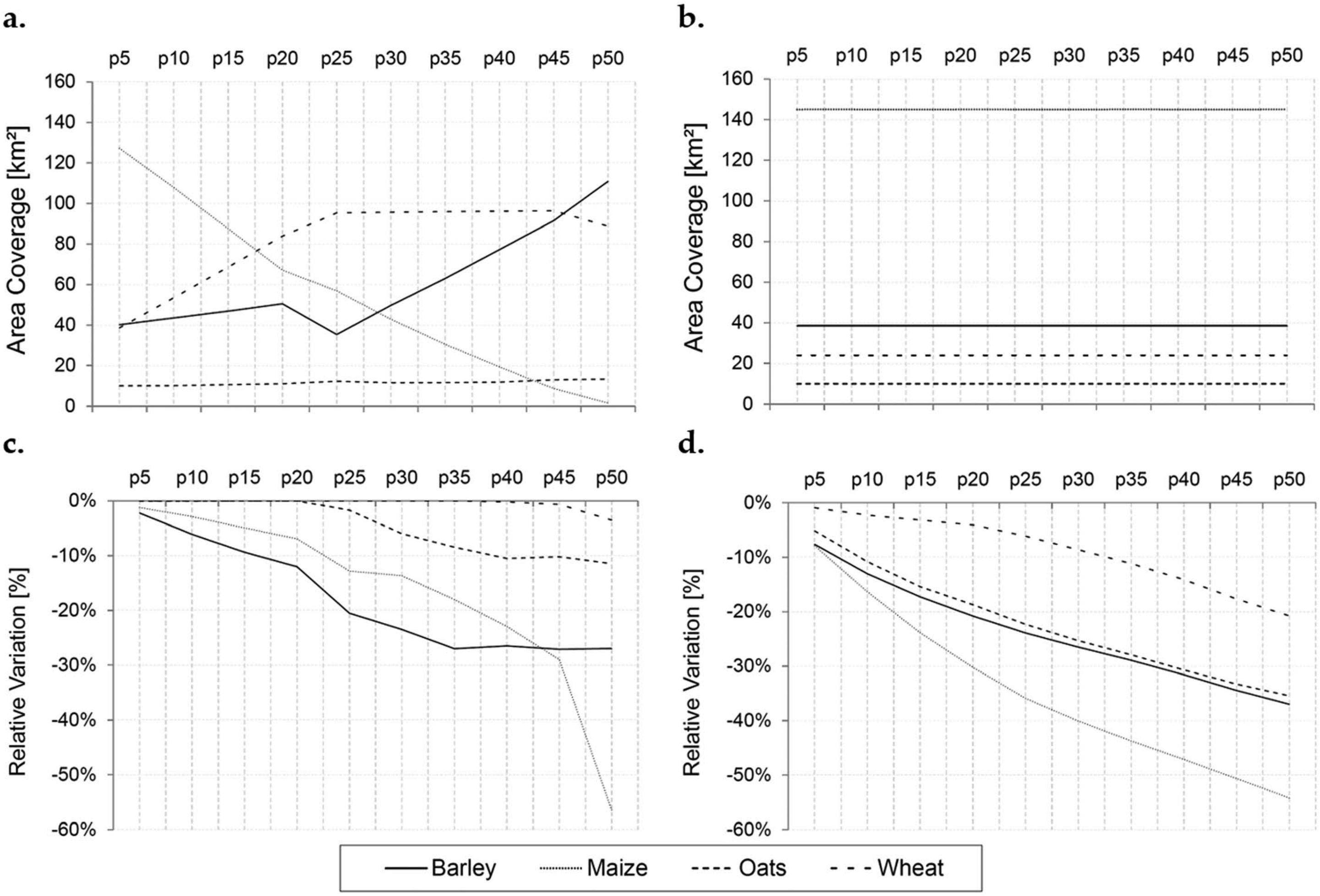

Figure 8. Graphical representation of how the crop area coverage and crop yields of the four dominant annual crops in the study area vary as a response to how socio-economic agents respond to the implementation of different irrigation restriction policies. On the top left (a), the crop area coverage responses under the adaptive scenario. On the top right (b), the crop area coverage responses under the nonadaptive scenario. On the bottom left (c), estimated crop yields variation under the adaptive scenario. On the bottom right (d), the crop yields responses under the nonadaptive scenario.

Socio-economic agents balance their crop portfolio aiming to maximize the utility derived from the provision of a range of attributes they value and with respect to a set of constraints. Figure 8a shows how farmers, following the methodology described in section 2.3, reallocate their land at a river basin scale as water available for irrigation is reduced following the implementation of an irrigation restriction policy. In general, for the crops depicted in Figure 8a, farmers switch from growing maize to either barley, wheat, or, at a lower scale, oats, depending on their utility function. By taking such action, farmers generally switch from higher to lower water intensive crops, while at the same time, maximizing their welfare, even though income, is generally affected by taking such adaptation measures (see Figure 5 for reference). Figure 8b depicts the evolution of the land distribution for the same crops when farmers are not allowed to choose their preferred alternative solutions. By ignoring agents' capacity to decide which crop to grow in alternative irrigation restriction scenarios, the stand-alone SWAT model results in lower crop yields and revenue (as depicted in Figure 9), larger utility losses, and suboptimal welfare.

Figure 8 also compares the two contrasting behavioral scenarios for the same four selected crops. When farmers are not allowed to change their crop portfolio (Figure 8d), the only way they can meet the water use reduction enforced by the irrigation restriction policy is to use less water for irrigation (i.e., deficit irrigation). In contrast, when farmers are able to change their crop portfolio (Figure 8c), the irrigation reduction target can be achieved by the combination of the total water demand per crops (i.e., crop selection) and the amount of water used for irrigation (i.e., deficit irrigation). As explained in section 3, irrigation

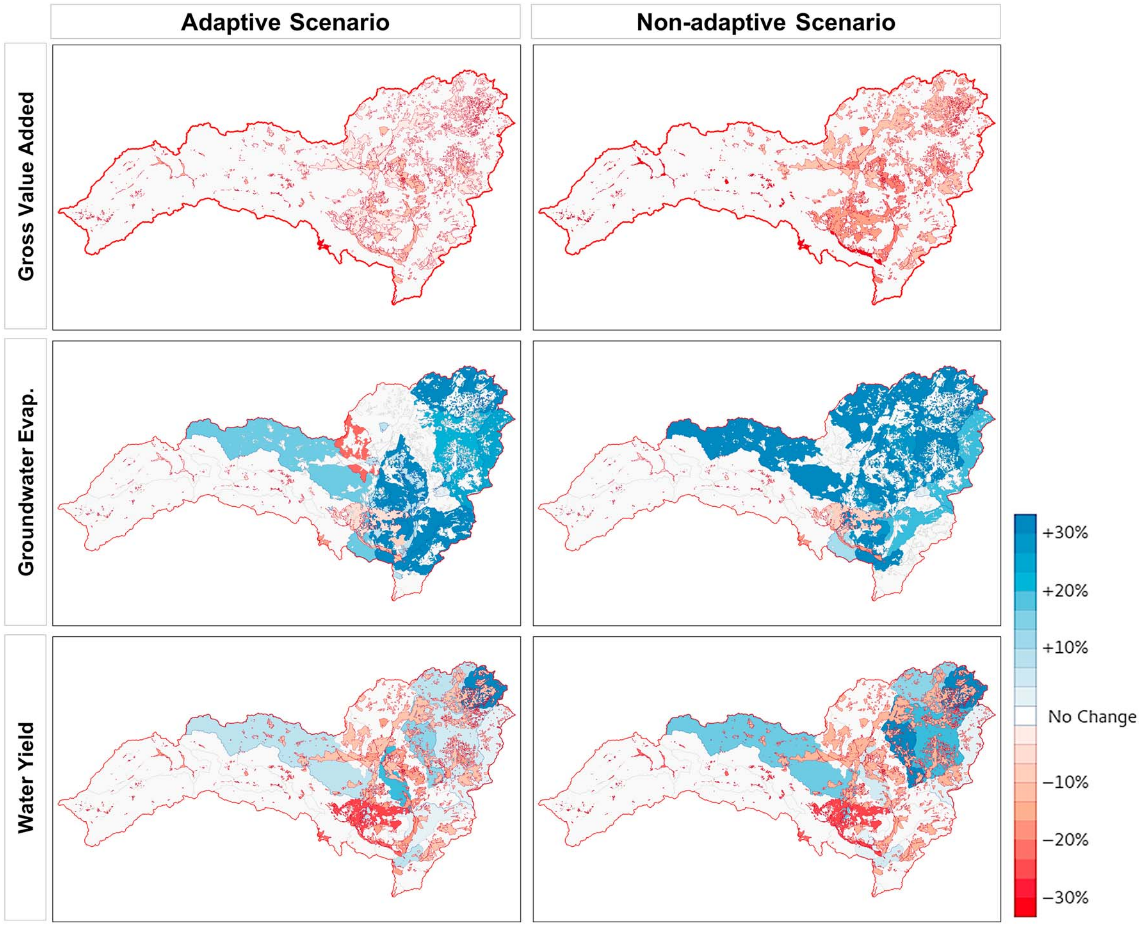

Figure 9. Relative estimated spatial variation of gross value added (first row), groundwater evapotranspiration (second row), and water yield (third row) processes for the irrigation policy restriction scenarios of 30% with respect to the baseline scenario. The maps on the left column represent the results under the adaptive scenario, while the maps on the right column display the responses under the nonadaptive scenario.

reductions are achieved at an AWDU scale, meaning that water available for irrigation is better allocated in a situation where farmers can adapt their crop portfolio as a response to a policy. This optimal allotment of water for irrigation results in generally higher crop productivity, as depicted in Figure 8c.

The two behavioral scenarios based on the ability of socio-economic agents to adapt to changes and to select their crop portfolio also have different spatially distributed impacts on the human and water systems, as shown in Figure 9.

The implementation of the considered irrigation restriction policy impacts the income of the socio-economic agents, as shown in Figure 5; however, when farmers are not allowed to define their crop portfolio as an adaptive measure to counteract the reduced access to water resources, higher economic impacts are observed. Figure 9 (first row) shows that across the whole basin, a reduction of 18.6% in GVA occurs in the scenario when farmers are deprived the ability to make decisions, while a lower reduction of 15.2% in the GVA is observed when farmers are able to make rational decisions. Moreover, when farmers are unable to adapt their crop portfolio, not only higher economic damages are observed but also their choices (or lack thereof) result in larger risk and management complexity, thus intensifying the reduction of farmers' utility.

The results shown in Figure 9 show that modeling the behavior of socio-economic agents also has hydrologic implications. When socio-economic agents are not allowed to define their crop portfolio as an adaptive response to the implementation of a restrictive irrigation policy, farmers are restricted to continue growing crops that usually demand more water than the amount of water to which they have access (see Figure 8 for reference). Consequently, the soil moisture drops, intensifying the soil moisture gradient between the underlying water table and the near-surface soils and the groundwater evapotranspiration flux. The results in the second row of Figure 9 show that basin-wide, the groundwater evapotranspiration flux is 1.47 million m^3/year higher under the nonadaptive scenario.

The groundwater evapotranspiration flux is also variable in space due to the connection with the crops' evapotranspiration demand and the water availability in the aquifer system; this means that the water availability in the aquifer systems is also tied to the crop portfolio of farmers. As discussed in section 3.3.2, the groundwater evapotranspiration flux is intensified in subbasins dominated by groundwater-fed irrigation (see Figure 4b for reference) due to the combination of the reduced depletion of the aquifer systems located in these subbasins and the reduced artificial supply of water by means of irrigation. When farmers are not allowed to select alternative crops, however, the groundwater evapotranspiration flux is further intensified due to a higher evapotranspiration deficit. The spatial variability of the groundwater evapotranspiration flux is represented in the second row of Figure 9.

The decision of which crop to grow in HERUs also affects hydrologic processes occurring at the surface; for example, the fraction of precipitation intercepted by vegetation and the evapotranspiration rate are functions of crop characteristics. Consequently, processes such as infiltration and surface runoff are also influenced by the decision of farmers in defining their crop portfolio. Combined, these processes contribute the total amount of water leaving the land surface and being converted to streamflow, which is quantified by the water yield and depicted in the third row of Figure 9. In general, water yield reductions inside AWDUs are slightly higher (1 to 2% in relative terms, 1 to 4 mm/year in absolute values) under the nonadaptive behavioral scenario. This is mainly due to the fact that the groundwater evapotranspiration is higher when farmers are deprived of decision-making capacity, meaning that more water is removed from the system by evapotranspiration rather than being converted to streamflow.

4. Conclusions

The complex dynamics of human and water systems requires innovative methodological frameworks capable of capturing the connections and feedback between these two systems. Where considered independently, changes in one system might have unforeseen consequences on the other. An example is the complex dynamics between agricultural and hydrological systems, where feedback from one system might affect the functionality of the other. In the microeconomic literature, behavioral responses in agricultural systems are typically driven by nonlinear utility functions whose outcome is conditional on information pertaining to a multiplicity of factors driving socio-economic processes. Reponses in hydrologic systems, in turn, depend not only on biogeophysical processes but also on interactions with agricultural systems.

Changes in governance and policy may affect the resilience of natural systems and trigger behavioral responses from socio-economic agents. The success of adaptive actions and policy design in social-ecological systems, hence, is determined by information on the dynamics of human-water systems; that is, how well the behavior (i.e., reasoning that guides the decision-making process) of socio-economic agents is understood with respect to a multitude of factors (be they social, economic, or hydrologic), and how socio-economic agents' responses affect the water system. While the understanding of complex human-water systems can be explored by means of socio-hydrology (i.e., by exploring the self-organization of people and its connections with the water system), the provision of information to support decision-making can be provided through means of modeling (e.g., systems analysis and DSS). As highlighted by Blair and Buytaert (2016), decision-making and policy formation are ultimately where (socio-hydrologic) model outputs can be put into practice to make a real difference.

This paper has contributed to the development of a socio-hydrologic inspired instrument by exploring a multifactor methodological framework aimed at connecting human and water systems under a common modeling framework. The proposed methodological framework utilizes the SWAT model as the eco-hydrologic module, while a PMAUP model is used as the microeconomics module. The socio-economic and eco-hydrologic modules are spatially connected and interact by means of a new common element, defined as the Hydrologic-Economic Response Units (HERUs). The dynamics of HERUs and related land use management, in turn, affects and is affected by responses from the coupled human-water system, which can feed back to the system through responses that impact on land and water management. Hence, the proposed methodological framework is suitable for the exploration of adaptation dynamics in complex human-water systems through land and water management. Using a similar methodological framework, other socio-economic and eco-hydrological models could be coupled and employed to support decision-making in different contexts, such as transboundary water management issues.

In order to explore the capabilities of the proposed methodological framework, a case study involving the assessment of the consequences in the coupled human-water system following the implementation of an irrigation restriction policy is presented. The selected case study area is the RMRB, in south-eastern Spain. The results obtained illustrate how decisions taken by socio-economic agents with regard to land management affect the water flow and hydrologic balance in the water system. Our findings highlight the relevance of considering the spatial connections between the socio-economic and eco-hydrologic processes occurring at the river basin scale in order to design successful water policies in complex human-water systems.

Although the results of this work are promising, the coupling of PMAUP and SWAT models explored in this paper has some limitations, in particular (i) labor, machinery, and other inputs prices, and output prices, are exogenous to the PMAUP model; (ii) spatial physical characteristics may only be indirectly taken into account when modeling socio-economic agents' behavior; and (iii) data availability constraints the range of choices, attributes, and the overall accuracy in the representation of socio-economic agents' behavior and responses.

The first limitation is a standard assumption in mathematical programming models, such as the PMAUP model, but still represents a significant limitation to the proposed model as structural shifts through major crop portfolio changes may be macroeconomically relevant, depending on the case study that is explored. On-farm adaptation to water rationing or other policies may impact aggregate farmers' choices, inputs used, and outputs produced. Where changes are marginal or happen at a small scale, these feedback can be ignored (as is the case study explored in this paper, since the economic relevance of the RMBM in the wider basin and regional scale is limited). However, where changes are not marginal, large-scale structural changes in the crop portfolio can lead to impacts on prices through feedback into the output of economic sectors at a regional and supraregional scale (Hertel & Liu, 2016). As the economy transitions toward a new equilibrium, commodity prices, including those relevant for agriculture, will change, thus affecting irrigators' decisions.

The second limitation refers to the spatial scale of socio-economic agents. Physical characteristics at a subspatial-level of socio-economic agents may not be fully taken into consideration for the calibration and modeling of agents' behavior (e.g., spatial variability of soil). Such information is implicitly considered in the calibration process with regards to real-life observations and is one of the reasons why importing relevant crops and land management techniques from nearby areas is problematic, as it may violate the PMAUP model's constraints (e.g., climate and soil). This means that the decision-making process of socio-economic agents does not take directly into account soil or topographic properties. However, by coupling the PMAUP model with a hydrologic model, these characteristics can then be used to estimate water availability, which is a factor that is directly taken into account by socio-economic agents in their decision-making process.

The third limitation refers to the calibration of the PMAUP model. In this paper, each possible combination of crops and management techniques are treated as unique crops within the crop portfolio of farmers. Since the model is calibrated using observed information, data availability constrains crop portfolio options. For example, if no information is available on the outcomes of deficit irrigation for a particular crop, the expected income or variability cannot be estimated, thus deficit irrigation for that particular crop is not a feasible option in the model. This is a known limitation of this data-intensive modeling approach that is acknowledged in section 2.1. In order to render this constraint less stringent, it is possible to consider the inclusion of relevant crops and management techniques from nearby areas, assuming that these can be adapted to the conditions of the case study, something that has been discussed in the second limitation above.

Finally, there are several improvements that can be made toward delivering a socio-hydrologic model that can assess the long-term dynamics of coupled human-water systems (e.g., co-evolution). In order to move in that direction, a wider economic and eco-hydrologic perspective is required. In economic terms, the incorporation of macroeconomic models that assess the behavior and response of socio-economic agents in the wider economy can provide the tools to explore the dynamics of markets and prices that drive adaptation processes in the longer term (Pérez-Blanco et al., 2016). Moreover, the incorporation of interactions among socio-economic agents at a microeconomic level could also provide the means for the identification of complex processes, such as emergence and self-organization (Ratter, 2012). Information on the institutional (rules and regulation capacity) and organizational investments (people and knowledge capacity) required to achieve water policy objectives is also necessary to understand institutions' adaptive ability and the range of policy options that can be realistically implemented, and to avoid path dependence and irreversibility (i.e., lock-in costs) and ensure adaptive robustness in policy design (Marshall, 2013). In eco-hydrologic terms, factors such as climate change and natural land-cover changes have to be taken into account (Pande & Sivapalan, 2017), as does the uncertainty in the hydrologic model. Explicit modeling of the groundwater dynamics is also needed to fully incorporate the effects of changes in groundwater elevations, storage, and fluxes (Bailey et al., 2016).

The methodological framework proposed in this paper aims to maintain the complexity of both agricultural and hydrologic systems, while targeting the exploration of the adaptation dynamics of socio-hydrologic systems. The key message conveyed by our research is that when representing coupled human-water systems, not only should the complexity of eco-hydrologic processes and their spatial variability be taken into account but also the complexity and spatial variability of socio-economic agents' behavior must be considered and conceptualized so that the relevant feedbacks between the systems can be accounted for.

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