Hydrol. Earth Syst. Sci., 28, 4501–4520, 2024
https://doi.org/10.5194/hess-28-4501-2024

Hydrology and
Earth System
Sciences
Open Access

Actionable human–water system modelling under uncertainty

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Received: 28 February 2024 – Discussion started: 8 March 2024
Revised: 3 June 2024 – Accepted: 8 July 2024 – Published: 14 October 2024

Abstract. This paper develops an actionable interdisciplinary model that quantifies and assesses uncertainties in water resource allocation under climate change. To achieve this objective, we develop an innovative socio-ecological grand ensemble that combines climate, hydrological, and microeconomic ensemble experiments with a widely used decision support system for water resource planning and management. Each system is populated with multiple models (multimodel), which we use to evaluate the impacts of multiple climate scenarios and policies (multi-scenario, multi-forcing) across systems so as to identify plausible futures where water management policies meet or miss their objectives and to explore potential tipping points. The application of the methods is exemplified by a study conducted in the Douro River basin (DRB), an agricultural basin located in central Spain. Our results show how marginal climate changes can trigger non-linear water allocation changes in the decision support systems (DSSs) and/or non-linear adaptive responses of irrigators to water shortages. For example, while some irrigators barely experience economic losses (average profit and employment fall by $<0.5\,\%$) under mild water allocation reductions of 5 % or lower, profit and employment fall by up to 12 % ($\sim 24\times$) when water allocation is reduced by 10 % or less ($\sim 2\times$). This substantiates the relevance of informing the potential natural and socio-economic impacts of adaptation strategies and related uncertainties for identifying robust decisions.

1 Introduction

Complex socio-ecological systems, including coupled human–water systems, are inherently difficult to manage (UNDRR, 2019). Periods of relative stability and predictability are interspersed with periods of unexpected, and sometimes abrupt, change (UNDRR, 2021). These changes, even if small, can create ripples that cascade across systems and generate non-trivial environmental and socio-economic impacts that are difficult to foresee – thus leading to uncertainty. We define uncertainty as a situation where “(1) it is not possible to identify all plausible futures, or (2) assign a probability to each identified plausible future” (Walker et al., 2003), which excludes probabilistic risk. Note that, while point (2) refers to uncertainty in modelling that can be quantitatively assessed, point (1) cannot and is accordingly not considered in our study (Knightian uncertainty[1]; Knight, 1921). Conventional consolidative modelling based on point

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[1] Walker et al. (2003) identify different levels across the uncertainty spectrum: (1) determinism (where point predictions are reliable), (2) probabilistic risk (we know which plausible futures lie ahead of us as well as the associated probabilities), (3) (deep) uncertainty type 1 (we do not know which inputs, parameters, and/or model structures are right, nor do we know their probability, but we can anticipate how the system will react to these), (4) (deep) uncertainty type 2 (we know we do not know), and (5) complete ignorance (we are not aware of what we do not know). Knightian uncertainty would fall into levels 4–5, which precludes modelling. Deep uncertainty type 1 can be modelled and has been modelled

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predictions and optimization of expected performance risks provides unrealistically precise information that gives a false appearance of uncertainty reduction (Hino and Hall, 2017). By ignoring (large parts of) the uncertainty inherent to modelling, the decision-making processes informed by conventional consolidative models can miss their objectives and under some conditions backfire and trigger crises (Anderies et al., 2006; Lempert, 2019). To allow humankind to embark on a sustainable and equitable development trajectory that delivers a satisfactory performance under multiple futures rather than a single plausible future (i.e. robust), a fundamental re-examination of the current approaches to modelling and uncertainty is necessary (IPCC, 2021). This calls for actionable forecasting methods that go beyond conventional consolidative models and point predictions and that thoroughly quantify and assess uncertainty so as to detect potential vulnerabilities of the system (including non-linearities) and identify robust adaptation policies and trajectories (UNEP, 2021).

The literature identifies three fundamental sources of uncertainty in models: (1) input uncertainty arising from scenario design and data inputs (Marchau et al., 2019), (2) parameter uncertainty associated with the data and methods used to calibrate model parameters (Tebaldi and Knutti, 2007), and (3) structural uncertainties associated with “the relationships between inputs and variables, among variables, and between variables and outputs” in models (Walker et al., 2003b). These uncertainties, which emerge within individual system models, can cascade across interconnected systems (UNDRR, 2019). Researchers have developed methods to quantify and assess scenario, parameter, and structural uncertainties in modelling, notably sensitivity analysis and multi-model ensemble experiments. Sensitivity analysis uses experiments representing the consequences of alternative sets of feasible assumptions (about scenario design, data, or parameter values) to discover their implications (Groves et al., 2015; Lempert and Groves, 2010), while multi-model ensemble experiments group multiple models with alternative structures to produce a range of forecasts rather than a single point prediction (CMIP6, 2023; ISIMIP, 2023). Sensitivity analyses and multi-model ensembles can be combined into “grand ensembles” that quantify input, parameter, and structural uncertainties within a system through the ensemble spread (Athey et al., 2019). This approach has been used in disciplines such as the climate sciences (e.g. Hagedorn et al., 2005; IPCC, 2014), economics (e.g. Krüger, 2017), and hydrology (e.g. Cloke et al., 2013). Recent research has combined grand ensembles over multiple ecological systems into multi-sector ensemble experiments such as the Coupled Model Intercomparison Project 6 (CMIP6) and the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) (CMIP6, 2023; ISIMIP, 2023). Echoing advances in socio-ecological research that have demonstrated the importance of considering the links between environmental change and human behaviour when designing and assessing solutions to complex climate, water, and other challenges (Pande and Sivapalan, 2017), multi-sector ensemble experiments have sought to incorporate human system aspects into their analyses. The conventional approach has been to exogenously model human systems through ensembles of macroeconomic models (typically integrated assessment models) and subsequently transform these simulation outcomes into scenarios of greenhouse gas emissions that can be used to force ensembles of climate system models (Ferrari et al., 2022). Alternatively, human systems can be endogenously represented in the socio-ecological ensemble by explicitly representing the impacts of ecological systems on human behaviour and responses and vice versa, e.g. using microeconomic models (Sapino et al., 2022b). Finally, acknowledging that model performance is conditional on its technical features as well as the modelling context and practices (Hamilton et al., 2019), research has paid attention to decision support systems (DSSs) and studied their design (Guillaume, 2022), output assessment (notably via robust decision-making, including multi-criteria evaluation; Groves et al., 2015; Maier et al., 2016; Marchau et al., 2019), and output interpretation (including the study of beliefs and biases, path dependence, incentives, politics and power, and information gaps and filtering; Cook et al., 2018; Peters and Nagel, 2020; Quiggin, 2012).

However, the application of these practices to human–water system modelling, management, and planning appears to be limited. In a recent literature review of uncertainty quantification in human–water system models (including DSSs used to support management and planning) across 198 studies, it was found that most studies focused on partial assessments of input (148 of 198 studies) or parameter uncertainties (40) through local sensitivity analysis, while structural uncertainties (7) were typically neglected (González-López et al., 2023). Few studies quantified two sources of uncertainty (31), and none quantified all three sources of uncertainty, which reflects the non-trivial computational costs of conducting multi-model and sensitivity analyses across multiple systems. Notably, 51 studies included a DSS or water resource management model such as WEAP or MIKE, of which 35 accounted for input uncertainty, 5 for parameter uncertainty, and 3 for structural uncertainty. Not a single study in the review, whether a DSS or another model, quantified uncertainties in both human and water systems (i.e. studies quantified uncertainties in either human or water systems). While integrated human–water system models (including DSSs) abound in the literature (Baccour et al., 2022; Graveline, 2020; Gil-García et al., 2023; Li et al., 2020; Martínez-Dalmau et al., 2023; Pande and Sivapalan, 2017; Ward, 2021) and examples of model intercomparison experiments (e.g. HEPEX, 2024) and sensitivity analyses do exist (Puy et al., 2022; Saltelli, 2019), particularly in wa-

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by model intercomparison projects such as AGMIP (2023), CMIP6 (2023), HEPEX (2024), and ISIMIP (2023).

ter systems, in practice water resource modelling (including DSSs for planning and management) ignores uncertainties within and across water and/or human systems (OECD, 2021). This is also observed in the wider natural resource literature, where multi-system model intercomparison experiments to quantify structural uncertainties address ecological (and non-human) systems (AGMIP, 2023; CMIP6, 2023; ISIMIP, 2023).

We argue that to develop water policies that are sensitive to climate change and other key sources of uncertainty, including the adaptive responses by human agents, it is necessary to deliver actionable interdisciplinary modelling that quantifies and assesses uncertainty. To achieve this objective, we propose an innovative human–water system grand ensemble that combines climate, hydrological, and microeconomic ensemble experiments with a widely used DSS for water resource planning and management, named AQUATOOL (Andreu et al., 1991). The proposed modelling framework is illustrated with an application that quantifies structural uncertainties and input uncertainties via climate change scenarios, although it can be expanded to quantify parameter and other input uncertainties (with non-trivial computational costs; see Sect. 4). In the first step, we use surface hydrology forecasts under alternative climate scenarios (representative concentration pathways RCP2.6, RCP6.0, and RCP8.5) obtained from ISIMIP to force the DSS AQUATOOL, which yields information on water allocation to water users in the basin. In a second step, we assess the adaptive responses by irrigators to water allocation decisions and their repercussions in terms of income, employment, and water and land use changes. The grand ensemble adopts a modular approach where models at each system level operate independently in modules, which are subsequently interconnected through sets of protocols, i.e. rules designed to manage relationships among modules (Essenfelder et al., 2018). Each system is populated with multiple models (multi-model), which we use to evaluate the impacts of multiple climatic scenarios and policies (multi-scenario, multi-forcing) across systems. The uncertainty range provided through the ensemble spread can reveal relevant trade-offs and vulnerabilities, including potential non-linearities, thus providing valuable information that can be used to revise strategies and policies, including by adapting models to account for expert feedback until a robust policy is agreed upon (Marchau et al., 2019). The methods are exemplified by an application to the Spanish part of the Douro River basin (DRB).

2 Case study area: the Douro River basin

The DRB in Spain covers an area of 78 889 km^2 and stretches over eight regions (NUTS2[2]), of which Castile and León is the most relevant (98.25 % of the basin's total area). The region experiences an average annual rainfall of 450–500 mm, with lower figures in the central part, where most of the agricultural area is situated, and higher precipitation in the mountainous areas surrounding the basin. Low rainfall values are complemented in agriculture with an expanding irrigation supply that, while representing 10 % of the total agricultural land, already claimed 89 % of the total water use of 4366×10^6 m^3 yr^{-1} in 2021 – which is expected to increase to 4692 and 4688 $\times 10^6$ m^3 yr^{-1} by 2027 and 2033, respectively, and which is mainly driven by irrigation expansion. Water supply on the other hand decreased from 14 231 $\times 10^6$ m^3 yr^{-1} over 1940–2005 to 12 777 $\times 10^6$ m^3 yr^{-1} over 1980–2005, and although on average this is still sufficient to meet the growing demand, drought spells are increasing in both frequency and intensity (Field et al., 2014). Agriculture, the main user and the one generating the lowest market added value from water, suffers most from water allocation restrictions as per the Spanish use priority rules established in the Drought Management Plans (DRBA, 2018).

Agricultural lands represent more than half of the Douro River basin's total area (5.7 $\times 10^6$ ha) and include rainfed crops such as wheat (26 %), barley (23 %), rye (2 %), sunflower (6 %), and vineyards (2 %). Irrigated crops include cereals such as maize (4 %), alfalfa (2 %), vegetables (1 %), and sugar beet (1 %). Surface water resources serve as the primary irrigation water source, representing on average 82 % of the basin's water supply (DRBA, 2022). The relevant administrative units for irrigation in the DRB (and in other regions in Spain) are the agricultural water demand units (AWDUs), which are also the agents in the microeconomic models.

3 Methods: a modular hierarchy of socio-ecological ensembles

We build a socio-ecological grand ensemble around AQUATOOL, a widely used DSS for watershed planning and management of water resource systems with applications to real planning cases in Spain, Ecuador, Brazil, Italy, Algeria, Mexico, Bosnia, Chile, Peru, Argentina, and Morocco, inter alia. The grand ensemble comprises four modules, each of which represents a key system in the human–water conundrum: the climate system, modelled by ISIMIP (2023) through an ensemble of global circulation models (GCMs); the natural water system, also modelled by ISIMIP (2023) through an ensemble of global hydrological models (GHMs); the water management system, modelled through an ensemble comprising alternative setups of the DSS AQUATOOL; and the human system, modelled through an ensemble of microeconomic mathematical programming models. The coupling among the modules is implemented in three steps (Fig. 2):

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[2] The European Union (EU) uses a system called NUTS (Nomenclature des Unités Territoriales Statistiques) to categorize its economic regions. In Spain, NUTS2 levels correspond to regional divisions (Eurostat, 2020).

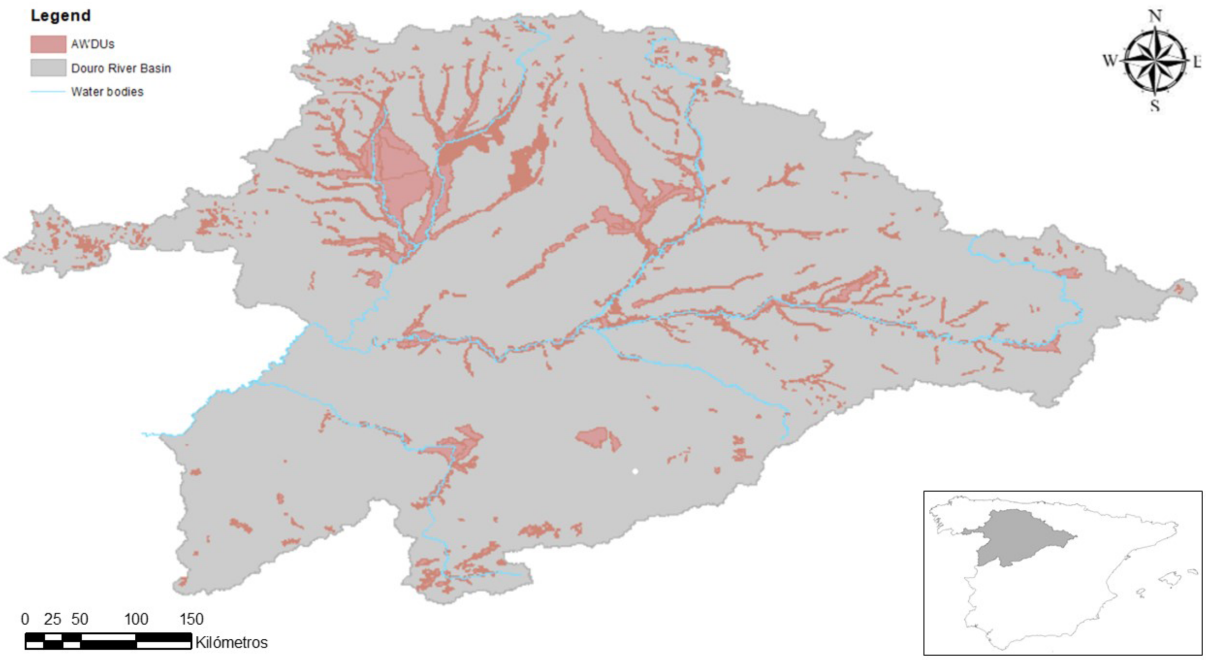

Figure 1. Localization of the DRB and detail of its AWDUs.

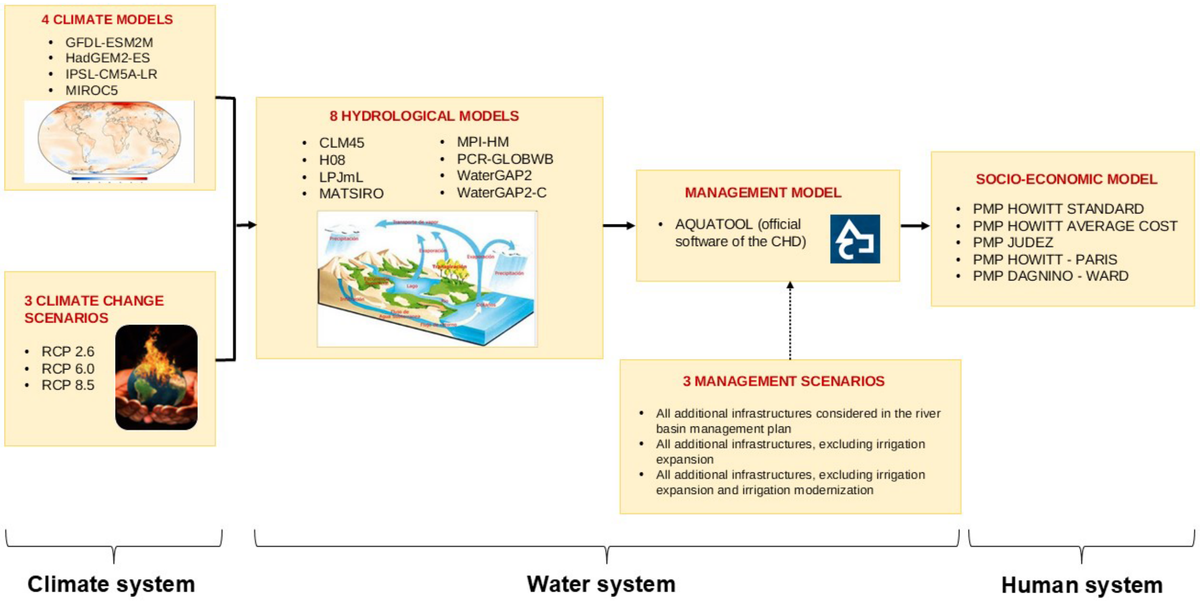

Figure 2. Human–water system grand ensemble.

- Step 1 is done externally to our model by ISIMIP Protocol 2b (2023) and includes the simulation of discharge data by forcing the ensemble of GHMs with climate change forecasts obtained from the ensemble of GCMs under alternative climate scenarios.
- Step 2 imports discharge outputs from the GHM ensemble into the AQUATOOL ensemble and produces data on water allocations under alternative water management scenarios.
- Step 3 uses water allocation data to force an ensemble of microeconomic models that represent human behaviour and responses and that simulate changes in land use, water use, income, and employment.

The upshot of this coupling process is a database of plausible futures that assesses the repercussions of climate change and adaptation scenarios for the water and human systems while accounting for input (climate and management scenarios), structural and parameter uncertainties in modelling, and cascading uncertainties across coupled ecological and human systems.

The following sub-sections describe the components of the grand ensemble, i.e. the climate scenarios (Sect. 3.1), the management scenarios (Sect. 3.2), and the modules, including the climate system (Sect. 3.3), natural water system (Sect. 3.4), water management system (Sect. 3.5), and human system modules (Sect. 3.6).

3.1 Climate scenarios

The modelling exercise encompasses three of the original four RCP scenarios. ISIMIP Protocol 2b (2023) considers RCP2.6, RCP6.0, and RCP8.5, which outline trajectories used by the IPCC (2021, 2014) to depict various potential climate futures based on future greenhouse gas emissions. In our simulations, for all the scenarios, we assumed present-day socio-economic conditions (2005 economic development, population levels, land use, and management consistent with the management scenarios in AQUATOOL).

- RCP2.6 outlines a climate scenario where CO_2 emissions decline to zero by 2100, with methane emissions at 50 % of 2020 levels and sulfur dioxide emissions at 10 % of 1980–1990 levels. Negative CO_2 emissions (e.g. via tree CO_2 sequestration) averaging $2\,\mathrm{Gt\,CO_2\,yr^{-1}}$ are incorporated. This pathway aims to keep global temperature rise below 2 °C by 2100.

- RCP6.0 foresees a peak in emissions by 2080, followed by a decline. It involves initially high greenhouse gas emissions and stabilization of radiative forcing post-2100, leading to a projected 3–4 °C temperature rise with CO_2 reaching 670 ppm.

- RCP8.5 depicts a scenario where emissions keep increasing throughout the 21st century, which is typically regarded as unlikely but still possible. Initially viewed as a worst-case scenario with overestimated coal emissions, it continues to be employed today to predict mid-century and earlier emissions based on existing policies.

3.2 Management scenarios

The water management ensemble comprises three different setups of the AQUATOOL model. Each model setup corresponds to one alternative management scenario with specific developments of reservoirs, canals, irrigated land, and irrigation infrastructure. These management scenarios are the outcome of the public consultation process led by the basin authority and implemented during the third river basin planning cycle (2022–2027), which crystalized in the DRB Management Plan (DRBA, 2022). In management scenario 1 (M01), all new developments proposed in the river basin plan are implemented. In management scenario 2 (M02), all new developments proposed in the river basin plan, excluding irrigation expansion, are developed. In management scenario 3 (M03), all new developments proposed in the river basin plan, excluding irrigation expansion and irrigation modernization, are developed. The specific developments carried out in each management scenario are detailed in Appendix A.

3.3 Climate system module

Climate change forecasts are produced by ISIMIP Protocol 2b (2023) by simulating the impacts of the three climate change scenarios (Sect. 3.1) using four GCMs. Each of the four GCMs is combined with each of the three RCP scenarios, thus generating 12 climate scenarios. The outputs from the GCMs are used, in turn, to force GHMs (see the next sub-section). The four GCMs are the following:

- GFDL-ESM2M combines atmospheric and oceanic circulation models, land dynamics, and biogeochemical processes like the carbon cycle. This model, a collaborative effort involving various institutions under the leadership of the Geophysical Fluid Dynamics Laboratory of the NOAA, aims to study climate and ecosystem interactions, both natural and human-induced. It includes components for the atmosphere, land, and oceans, tracking factors such as aerosols, precipitation, and sea ice dynamics. The model also monitors chemical and ecological tracers that impact nutrient cycles, plant growth, and more. By integrating these components, GFDL-ESM2M provides comprehensive understanding of how Earth's ecosystems interact with the climate system. For additional details and a mathematical statement, the reader is referred to Dunne et al. (2013, 2012).

- HadGEM2-ES is part of the broader HadGEM2 model family involving diverse model setups that vary in complexity while sharing a unified physical structure. This version of the HadGEM is the second generation and includes, among other features, a well-resolved stratosphere. The HadGEM is developed in the Hadley Center and the Met Office (UK) and is one of the most well-known full global climate models. For additional details and a mathematical statement, the reader is referred to Collins et al. (2011).

- The IPSL-CM5A-LR model is a comprehensive and full Earth system model (ESM) and is developed at the Institut Pierre-Simon Laplace (IPSL) (France). The model offers a versatile platform for addressing diverse scientific questions. It comprises two sets of physical models, including ocean extensions. The model's configurations can vary in terms of physical parameterizations, resolution, components (ranging from the atmosphere and land to a full ESM), and processes (covering physical, chemical, aerosol, and carbon cycle processes). At its core, IPSL-CM5 integrates components for the land surface, atmosphere sea ice, and ocean, along with biogeochemical processes, including stratospheric and tropospheric chemistry, aerosols, and terrestrial and oceanic carbon cycles. For additional details and a mathematical statement, the reader is referred to Dufresne et al. (2013).

- MIROC5 (Model for Interdisciplinary Research on Climate version 5) is an atmospheric and oceanic GCM developed at the Atmosphere and Ocean Research Institute of the University of Tokyo (Japan). MIROC is an advanced climate model designed to better simulate the average climate, variability, and climate change resulting from human-induced radiative forcing. This model was tested through a 100-year long control experiment with specific atmospheric and oceanic resolutions, and its performance was compared to observations and a previous model version with varying spatial resolutions. For additional details and a mathematical statement of the model, the reader is referred to Watanabe et al. (2010).

3.4 Natural water system module

Water discharge forecasts are produced by ISIMIP Protocol 2b (ISIMIP, 2023) forcing eight GHMs with the simulation outputs of the four GCMs. GHMs provide spatially aggregated information within standardized grids of 0.5° × 0.5°. The eight GHMs are the following:

- CLM4.5 explores the cycling of water, trace gases, chemical elements, and energy. The model components include biogeophysics, the hydrological cycle, dynamic vegetation, and biogeochemistry. The land surface is categorized into glacier, lake, wetland, urban, and vegetated areas, with further sub-divisions for plant functional types. For additional details and a mathematical formulation, the reader is referred to Oleson et al. (2013).

- H08 represents a global hydrological model organized by grid cells, featuring six sub-models designed to explicitly replicate the interplay between the natural water cycle and human activities worldwide. The model maintains a nearly complete water balance. In 2016, water abstraction schemes were improved, and a groundwater scheme was added. CLM4.5 in ISIMP Protocol 2b is run using inputs from the climate models: IPSL-CM5A-LR, HadGEM2-ES, GFDL-ESM2M, and MIROC5. For additional details and a mathematical statement of the model, the reader is referred to Hanasaki et al. (2018).

- LPJmL is a model that focuses on water balance and irrigation processes, with the latest version distinguishing between different irrigation systems. It is designed to study the impact of replacing natural vegetation with agroecosystems due to rising CO_2 levels and climate change. Additionally, it plays a key role in assessing future ecosystem services, considering factors like climate, CO_2 levels, land management, and land use change. LPJmL in ISIMP Protocol 2b is run using inputs from the climate models: IPSL-CM5A-LR, HadGEM2-ES, GFDL-ESM2M, and MIROC5. For additional details and a mathematical statement of the model, the reader is referred to Bondeau et al. (2007).

- MATSIRO is meant to work with a climate system research model. It is used for climate studies covering various timescales and resolutions. MATSIRO focuses on representing essential land–atmosphere water and energy exchange processes in a physically based yet straightforward manner, making it a valuable tool for climate research. MATSIRO in ISIMP Protocol 2b is run using inputs from the climate models: IPSL-CM5A-LR, HadGEM2-ES, GFDL-ESM2M, and MIROC5. For additional details and a mathematical formulation of this model, the reader is referred to Takata et al. (2003).

- MPI-HM is a model that focuses solely on calculating water fluxes, excluding any considerations for energy balance calculations. MPI-HM is used for high-resolution river routing in hydrological research. MPI-HM in ISIMP Protocol 2b is run using inputs from the climate models: IPSL-CM5A-LR, GFDL-ESM2M, and MIROC5. For additional details and a mathematical statement, the reader is referred to Stacke and Hagemann (2012).

- PCR-GLOBWB is a model that simulates water dynamics for each grid cell on a daily basis. It tracks water storage in soil and groundwater layers as well as exchanges like infiltration, percolation, and capillary rise. The model includes atmospheric interactions, such as rainfall and evapotranspiration, and connects water use in agriculture, industry, and households to daily hydrological processes. The simulated runoff and water flow are subsequently routed through river networks interconnected with water allocation and reservoir operation schemes. PCR-GLOBWB in ISIMP Protocol 2b is run using inputs from the climate models: IPSL-CM5A-LR, HadGEM2-ES, GFDL-ESM2M, and MIROC5. For additional details and a mathematical statement, the reader is referred to van Beek and Bierkens (2009).

- WaterGAP2 and WaterGAP2-2C are global freshwater models that assess water flows and storage across continents, factoring in human impact from water abstractions and reservoirs. It helps analyse water scarcity, droughts, floods, and the influence of human actions on groundwater, wetlands, streamflow, and sea level rise. The model relies on climate data, surface water information, land characteristics, and more for its inputs. WaterGAP2 and WaterGAP2-2C in ISIMP Protocol 2b are run using inputs from the climate models: IPSL-CM5A-LR, HadGEM2-ES, GFDL-ESM2M, and MIROC5. For additional details and a mathematical statement of the model, the reader is referred to Alcamo et al. (2003).

3.5 Water management system module

AQUATOOL serves as a DSS designed for editing, implementing, reviewing, and analysing hydrologic models, with a specific emphasis on integrated watershed management. It provides detailed data on the qualitative and quantitative conditions of water bodies as well as water allocation, across both space and time. AQUATOOL is structured into various modules, each with its own model or software. In our application to the DRB, we utilize the AQUATOOL module to conduct a comprehensive longitudinal and spatial analysis of the impacts of climate change and discharge variations in alternative management scenarios on water bodies and water allocation. The impacts of climate change models and management scenarios on surface water bodies are simulated according to continuity or equilibrium principles, while both unicellular and multicellular models are used for groundwater bodies. The water allocation, on the other hand, is determined by relying on a network optimization algorithm. The model is calibrated following a positive approach that aims to minimize the difference between simulated and observed water allocations, observed discharges, and reservoir levels (PUV, 2020).

The data inputs for setting up AQUATOOL in the DRB are accessible online (Mírame-IDEDUERO, 2023), excluding the discharge series under natural conditions for the model baseline conditions (no climate change), which must be generated. To obtain these discharge series under natural conditions, daily precipitation series from 1940 to 2018 are processed using the EVALHID tool (Lerma et al., 2017), in addition to SIMPA (Sistema Integrado para la Modelación del proceso Precipitación Aportación) (CEDEX, 2020).

AQUATOOL is openly accessible for academics and practitioners, while private for-profit companies have to pay a fee.

3.6 Human system module

The human system module is comprised of an ensemble of five positive mathematical programming (PMP) models. PMP modelling also adapts a positive calibration approach capable of reproducing the choices of the reference year without error. PMP was first formalized by Howitt (1995) and has since been the dominant technique for calibrating mathematical decision-making models in the agricultural sector. In general, these models include a non-linear component within the objective function, which can be yield or cost. The original parameter, yield (y_i) or cost (c_i), is replaced with a crop-area-dependent function ($c_\mathrm{i} = \alpha_\mathrm{i} + \frac{1}{2}\beta_\mathrm{i} x_\mathrm{i}$ or $y_\mathrm{i} = \mathrm{B0_i} + \mathrm{B1_i} x_\mathrm{i}$), so that when the area of a crop (x_i) expands, its yield decreases (its cost increases) and vice versa, with $\mathrm{B0_i}$, $\mathrm{B1_i}$, α_i, and β_i being the calibrating parameters (intercept and slope) for yield and cost linear functions.

Five alternative different PMP calibration techniques have been included in the human system ensemble, i.e. the standard approach of Howitt (1995), the average cost approach (Heckelei et al., 2000), the Paris (1988) approach, the Júdez et al. (2001) approach, and the Dagnino and Ward (2012) approach, which we briefly introduce below. For a detailed description and mathematical statement of the model, the reader is referred to the original papers. While all of these approaches reproduce the reference or calibration year without error, the objective function and agent responses during the simulations do differ, often significantly.

- Standard approach (Howitt, 1995). The original work included a yield function, which in this case has been replaced by a cost function. This method needs two stages to calibrate. First, the dual values (μ_i) of some calibration constraints are obtained using a linear model. From these dual values, the observed cost ($\mathrm{cost}_\mathrm{i}^0$) and the observed area (x_i^0), the calibration coefficients of the cost function (α_i and β_i) are obtained. As noted by Heckelei et al. (2000), a key problem with the standard approach is the under-determination of the calibration parameters.

- Average cost approach (Heckelei et al., 2000). The average cost approach is similar to Howitt (1995), but the calibration parameters are determined in such a way that, for the reference year, the value of the cost function coincides with the observed average cost.

- Paris (1988) eliminates the first calibration parameter.

- Judez et al. (2001) skip the first phase of Howitt's method and rely on external information to calibrate the model, land rent (LandRent), and average income per crop ($\mathrm{AverageIncome_i}$).

- Dagnino and Ward (2012) also skip the first phase and directly calibrate a yield function with the parameters $\mathrm{B0_i}$ (intercept) and $\mathrm{B1_i}$ (slope) from the observed yield ($\mathrm{yield}_\mathrm{i}^0$), average income ($\mathrm{AverageIncome_i}$), and price per crop ($\mathrm{price_i}$).

All the models maximize a quadratic objective function where the only relevant attribute is profit, as measured by the profit, subject only to soil and water constraints. The data used for the calibration of the five PMP models are available in Table S1 in the Supplement.

3.7 Results

We conduct a set of simulations in three steps, following the hierarchy detailed in Fig. 2. Step 1, which is performed exter-

Table 1. PMP calibrating parameters by method.

	Linear calibrating parameter	Quadratic calibrating parameter
Standard approach	$\alpha_\mathrm{i} = \mathrm{cost}_\mathrm{i}^0$	$\beta_\mathrm{i} = \frac{\mu_\mathrm{i}}{x_\mathrm{i}^0}$
Average cost approach	$\alpha_\mathrm{i} = \mathrm{cost}_\mathrm{i}^0 - \mu_\mathrm{i}$	$\beta_\mathrm{i} = \frac{2\mu_\mathrm{i}}{x_\mathrm{i}^0}$
Paris approach (1988)	$\alpha_\mathrm{i} = 0$	$\beta_\mathrm{i} = \frac{\mathrm{cost}_\mathrm{i}^0 + \mu_\mathrm{i}}{x_\mathrm{i}^0}$
Judez et al. (2001)	$\alpha_\mathrm{i} = \mathrm{cost}_\mathrm{i}^0 - \frac{1}{2}\beta_\mathrm{i} \cdot x_\mathrm{i}^0$	$\beta_\mathrm{i} = \frac{2 \cdot \mathrm{AverageIncome}_\mathrm{i} - \mathrm{LandRent}}{x_\mathrm{i}^0}$
Dagnino and Ward (2012)	$\mathrm{B0}_\mathrm{i} = \mathrm{yield}_\mathrm{i}^0 - \mathrm{B1}_\mathrm{i} \cdot x_\mathrm{i}^0$	$\mathrm{B1}_\mathrm{i} = \frac{-\mathrm{AverageIncome}_\mathrm{i}}{\mathrm{price}_\mathrm{i} \cdot x_\mathrm{i}^0}$

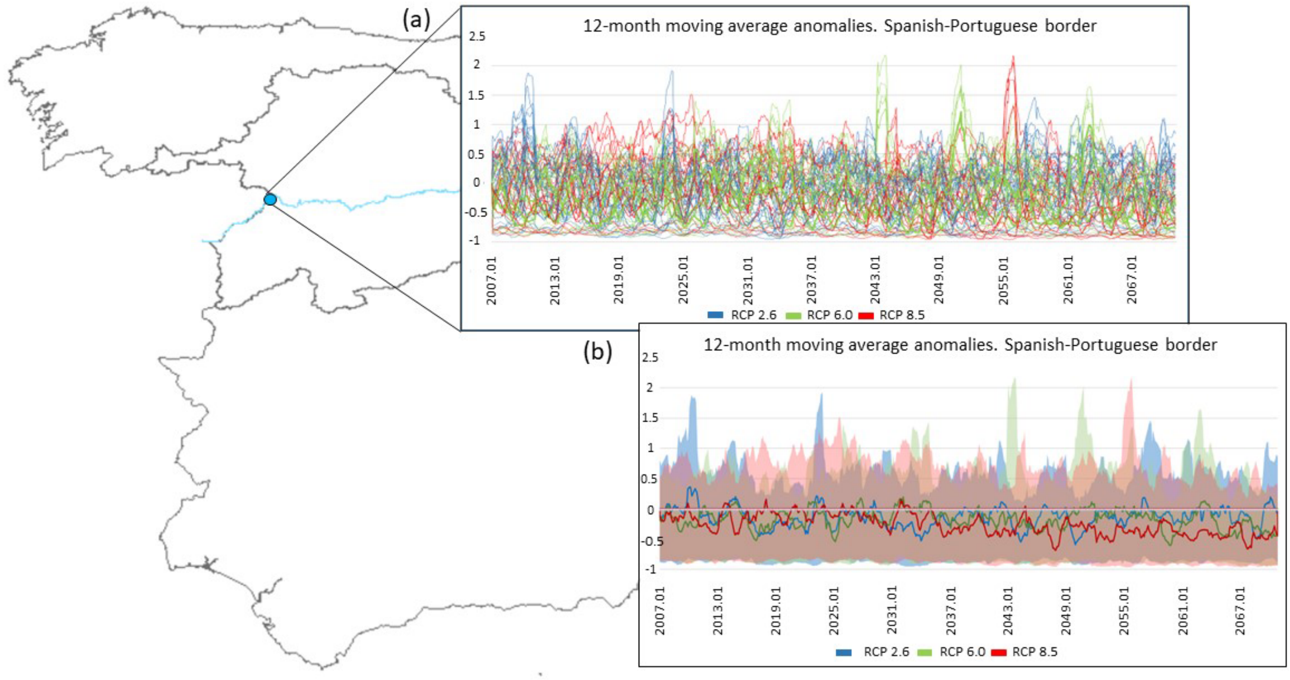

Figure 3. **(a)** Longitudinal discharge anomalies on the border between Portugal and Spain (moving average of 12 months). **(b)** Ensemble spread and best estimate of discharge anomalies for the border between Portugal and Spain, with a moving average of 12 months.

nally to our model by ISIMIP (2023) Protocol 2b, produces discharge data by forcing eight GHMs with climate change forecasts produced by an ensemble of four GCMs in three climate change scenarios. This results in 86 plausible futures (note that not all GHMs can run simulations using the outputs produced by the GCMs, as explained in Sect. 3.4). Discharge data are produced in regular grids of $0.5° \times 0.5°$ and are transformed into discharge anomalies (%) by comparing GHM forecasts under climate change (2006–2040 and 2006–2070 periods) to simulations using historical data (45 years in historical series from 1961 to 2005). Figure 3 illustrates longitudinal discharge anomalies for a critical section of the basin on the border between Portugal and Spain, using a 12-month moving average. Most combinations of models and scenarios in Fig. 3 forecast a reduction in discharge. Discharge reductions exhibit a more significant impact during the 2040–2070 period compared to the earlier 2006–2040 period, which is exacerbated by the peak in greenhouse gas concentrations and the worsening effects of climate change on the water cycle.

In Step 2, anomalies in discharge reported by GHMs are imported into the water management system ensemble to obtain longitudinal series of water allocation for each AWDU in three alternative management scenarios (see Sect. 3.2). To this end, we follow the approach by MAGRAMA (2017) to adjust the discharge series under natural conditions in AQUATOOL using the discharge anomalies obtained in Step 1. The resulting water allocations for each of the 150 AWDUs in the Castile and León region and every year in the series are reported in Table S2 in the Supplement. The integration of the ensembles of the climate system, natural water

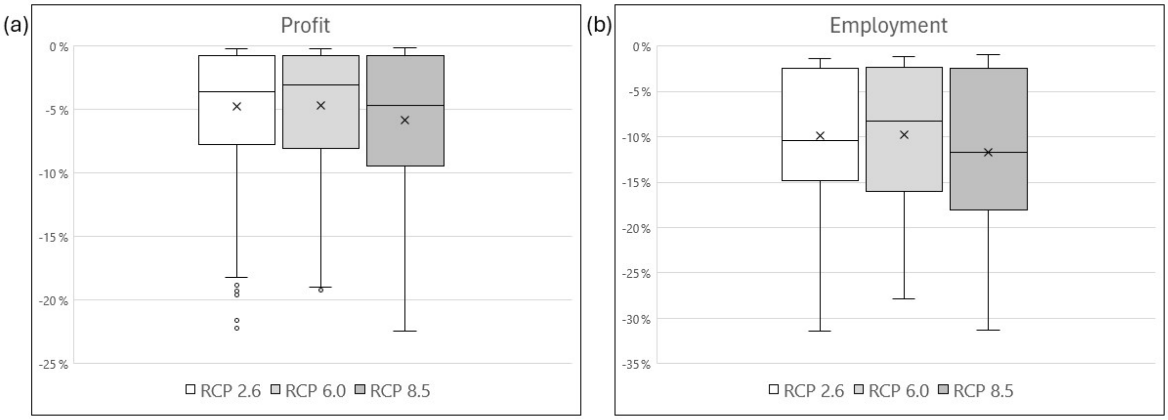

Figure 4. Box–whisker plots for **(a)** profit and **(b)** employment under RCP2.6, RCP6.0, and RCP8.5.

system, and water management system further amplifies the database of plausible futures to 258.

Finally, in Step 3, each of these 258 plausible futures and related water allocations to AWDUs is used to force the human system ensemble and produce longitudinal forecasts of the impacts of climate change and water management strategies on the income and employment for each of the AWDUs in the DRB. The box–whisker plot in Fig. 4 quantifies the uncertainty across the entire basin for each RCP scenario (RCP2.6, RCP6.0, and RCP8.5) for both profit and employment. In Fig. 4a, the change in profit shows greater dispersions and outliers in the RCP2.6 scenario, while the RCP6.0 and RCP8.5 scenarios display distributions that are more concentrated around the median. In all cases, the median is negative, indicating a reduction in profits in each scenario. In Fig. 4b, changes in employment also exhibit a negative trend in the median across all the RCP scenarios. The data dispersion is greater in the RCP8.5 scenario, followed by RCP6.0 and RCP2.6, suggesting increased variability in employment changes as greenhouse gas concentrations rise. Figure 4a and b reflect an adverse impact on both profit and employment as the RCP scenarios progress, with more pronounced effects in scenarios with higher greenhouse gas concentrations (RCP8.5).

The presented box–whisker plot lacks spatial disaggregation of the results, thus constraining our understanding of spatial variations within the basin. To address this limitation, Fig. 5 exemplifies the modelling potential in delivering spatially distributed profit outcomes. This figure presents the impacts of climate change on profit for each of the five PMP models, considering one adaptive management strategy (M03) and three climate scenarios (RCP2.6, RCP6.0, and RCP8.5) over the period 2006–2070 and for each of the AWDUs in the DRB. Such spatial representation allows for the identification of regional patterns and trends that remain elusive in the aggregate analysis, which is of value for local planning and management by pinpointing specific areas necessitating attention or adaptation. Detailed results of the climate change impacts on profit and employment for each AWDU, management strategy, and climatic scenario are available in Appendix B. Additionally, Table S3 in the Supplement provides longitudinal projections of profit and employment for each ensemble model and AWDU.

For all AWDUs, all combinations of models and scenarios predict a reduction in profit and employment due to climate change. Profit and employment losses are higher for 2040–2070, when greenhouse gas concentrations peak and discharge reductions are more marked. Notably, employment and profit losses are significantly higher in management scenario M01 than in M02, which in turn also displays higher employment and profit losses than M03. This indicates that the expansion of irrigation (incorporated into M01) and its modernization (M01, M02) negatively affect both profit and employment. This is due to the reallocation of water resources from downstream to upstream users, resulting in a cascade of negative and sometimes non-linear repercussions that diminish overall profit and employment losses.

AWDUs in the DRB initially manage decreases in water allocations by replacing irrigated crops at the margin (wheat) with rainfed crops, so as to maintain the surface area dedicated to valuable irrigated crops like sugar beet, vegetables, maize, and fruits. As water allocations continue to decline, AWDUs are constrained to decrease the surface area of increasingly valuable irrigated crops, resulting in more abrupt profit reductions. Due to the labour-intensive nature of these crops, employment also undergoes sudden changes. This explains why marginal decreases in water allocation can lead to substantial and sometimes disproportionately larger decreases in profit and employment, contributing to a considerable degree of non-linear change. For instance, AWDUs in the Carrión sub-basin (AWDUs 2000063, 2000064, 2000065, 2000082, 2000083, 2000084, 2000085, 2000086, 2000097, 2000099, and 2000105 – see Table S3) can initially manage reductions in water allocation of up to 10 % with low

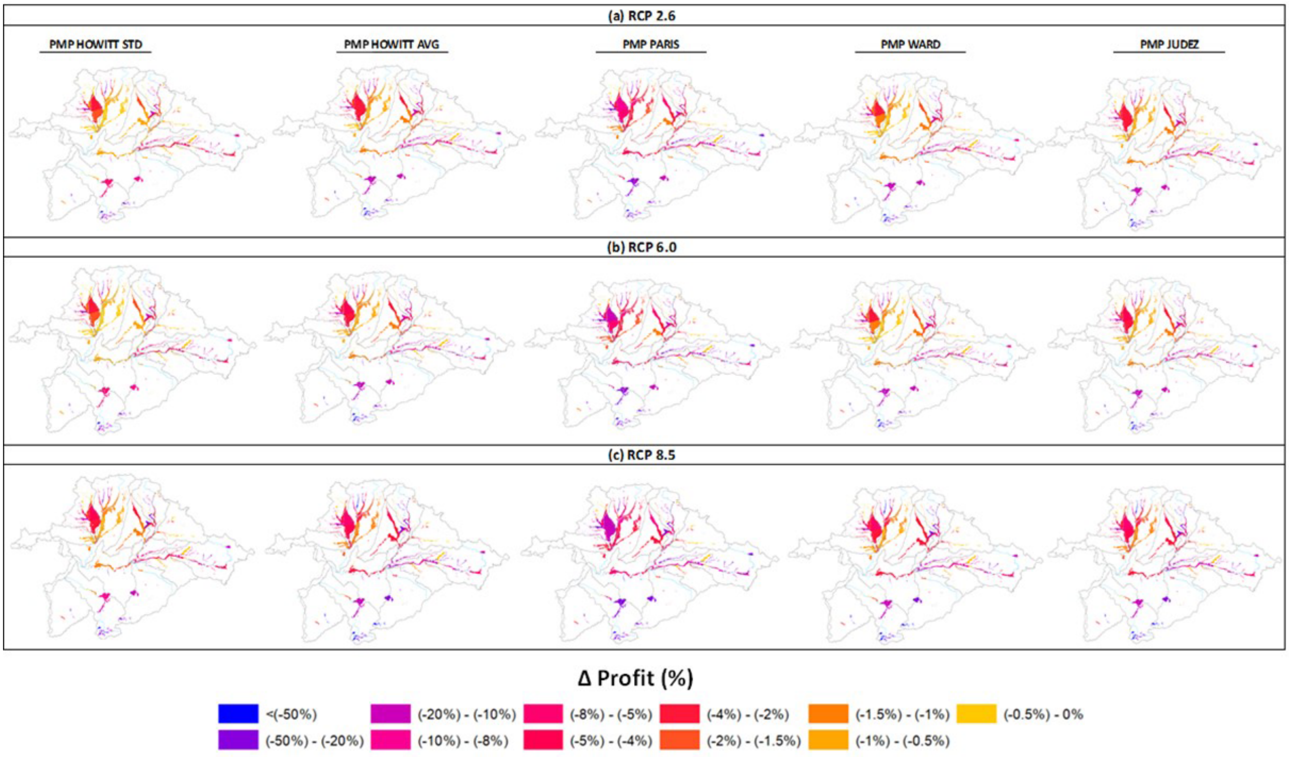

Figure 5. Spatially disaggregated impacts (best estimates) of discharge anomalies under climate change (**a** RCP2.6, **b** RCP6.0, **c** RCP8.5) on profit in the AWDUs of the Douro River basin for the 2006–2070 periods, considering the management scenario M03. Changes in profit are obtained as the difference between simulated and observed values in the year 2017. It is important to note that the GHM MPI-HM yields discharge forecasts that are markedly lower than those obtained with the other models, leading to outliers in the employment and profit predictions, which decrease by nearly 100 % in most of the years in the series. This outlier is excluded from the best estimates reported in this figure.

to moderate economic losses ($< 5\,\%$). However, they experience abrupt decreases in profit and employment of up to 40 % under more stringent water allocation reductions of around 20 %. Similarly, AWDUs in the Arlanza sub-basin (AWDUs 2000077, 2000078, 2000079, 2000080, 2000235, 2000320, 2000338, and 2000603 – see Table S3), with minimal economic losses ($< 0.5\,\%$) under mild water allocation reductions of 5 % or lower, experience abrupt decreases in profit and employment of 12 % when water allocation is decreased by 10 %. These complex interactions between human behaviour and the water system, including non-linear responses by economic agents to environmental change, cannot be fully understood or modelled without considering the economic system. To this end, coupled socio-ecological modelling is necessary – although this can further amplify uncertainty, especially if more than one human system model is used.

4 Discussion and conclusions

This paper introduces a modular hierarchy comprising ensembles of socio-economic and ecological systems (multi-system ensemble). Each ensemble incorporates multiple models (multi-model ensemble) employed to evaluate the repercussions of climate change and management scenarios for water availability, profit, and employment (multi-model ensemble). Using this modelling approach, a comprehensive database of simulations is generated, wherein each result represents the socio-economic and environmental implications of a distinct combination of scenarios and models, thus quantifying parameter, structural, and scenario uncertainties. By integrating human system dynamics into the modelling framework, the resulting grand ensemble accounts for non-linearities emerging across both human and water systems as well as their cascading impacts, thus providing valuable data for informing robust strategies.

The grand ensemble is built around a commonly used DSS model, AQUATOOL, thus contributing to the generation of actionable science that can be readily adopted by decision-makers and other stakeholders. The coupling framework is intentionally crafted to be reproducible and adaptable, with the ability to incorporate alternative climate, hydrological, DSS, and microeconomic models of farmers that may better represent climate, water, and/or human systems in different regions. Accordingly, our coupling approach and modelling framework can be applied widely and at a relatively low cost by exploiting existing data and/or models. To better inform the replication of our framework elsewhere, we exemplify below which models can be used to populate our framework at each system level.

- Climate system and natural water system: climate forecasts for alternative climate scenarios are available in climate ensemble experiments, including global (CMIP6, 2023; ISIMIP, 2023) and downscaling (EURO-CORDEX, 2023) experiments at a regional level, which offer simulation outputs for key climate change scenarios such as RCP2.6 or RCP6.0. Managing these simulation outputs requires skills in big data, knowledge of NetCDF and related software, knowledge of the format in which simulations are reported, and elemental knowledge of climate model simulation. Climate ensemble experiments can provide relevant data on water discharge, a key input for the water management system. Water discharge data can alternatively be produced using regionally calibrated models, which requires ad hoc data-gathering efforts (although some of these models also provide databases for their calibration) and modelling skills in the specific software to be used. Also, a list of the hydrological models included in Pérez-Blanco et al. (2022) could be incorporated: the Soil and Water Assessment Tool – SWAT (Arnold et al., 1998); the Annualized Agricultural Non-Point Source Pollution Model – AnnAGNPS (Young et al., 1989); the Areal Nonpoint Source Watershed Environment Response Simulation – ANSWERS 2000 (Bouraoui and Dillaha, 2000); the Agricultural Policy/Environmental eXtender model – APEX (Gassman et al., 2009); the US Army Corps of Engineers Hydrologic Engineering Center Hydrologic Modeling System – HEC-HMS (US Army Corps of Engineers, 2015); and the Soil and Water Integrated Model – SWIM (Krysanova et al., 2005).

- Water management system: the data inputs necessary to run the relevant DSS in a given basin are typically accessible to the competent authority, either directly or through a consulting company. Some widely used DSSs that could be incorporated into our modelling framework include AQUATOOL, WEAP, TOPKAPI, MIKE, RIBASIM, or LISFLOOD. Critically, DSSs are often profusely edited to account for the unique features of the basin at hand, and thus their management requires support from an expert. In our illustrative example with AQUATOOL, the competent authority was the DRB, which typically relies on an external consultant to run hydrological simulations of the management and allocation of water resources. For this research, USAL collaborated with the consultant to develop the coupling and run the simulations, leveraging funding provided by the DRB.

- Human system: the human system can be populated by any mathematical programming model of agricultural water use available in the literature. The data necessary to run these models are provided in Table S1. In the case of EU river basins, all necessary data are publicly available, although the granularity may differ. For example, in the case of the Portuguese part of the DRB, a similar database to the one used in this paper is publicly available, although the granularity is significantly lower (regional scale rather than AWDU scale).

The current and previous (Gil-García et al., 2023; Pérez-Blanco et al., 2021a, b) versions of the AQUATOOL-based human–water system DSS presented in this paper have already been used by stakeholders in the context of financial and economic viability assessments of new water works proposed in the Douro River Basin Plan under climate change and uncertainty, including La Rial reservoir, Los Morales reservoir, the Lastras de Cuéllar reservoir (assessed with previous versions of the model with a focus on input uncertainty), and the Las Cuezas reservoirs (assessed with the current version of the model that includes structural uncertainties in models). All of these assessments were commissioned by the river basin authority.

Future scientific research offers several avenues to further develop and expand the proposed hierarchical coupling framework for understanding the intricate interactions between human actions, water resources, and related uncertainties. Firstly, it is possible to introduce improvements to the individual models within each module by integrating recent scientific advancements within each discipline. For instance, recent developments in microeconomic modelling decouple land use choices from water use choices, allowing for two decision variables rather than one decision variable, as is usually the case in conventional PMP and other mathematical programming models, where agents only decide on land use (Graveline and Merel, 2014; Loch et al., 2020; Sapino et al., 2022a). This allows for the representation and assessment of adaptation measures at the intensive margin (such as deficit or supplementary irrigation), going beyond the extensive (transition to less water-intensive crops) and super-extensive (transition to rainfed crops) adaptations examined in conventional PMP and other mathematical programming models.

Secondly, additional protocols could be introduced across systems to bolster the framework and its interactions. For instance, this might entail incorporating distinct protocols for water use decisions independent of land use decisions in the coupling between the human and hydrological modules.

Thirdly, the modelling framework could benefit from the integration of extra modules, including the linkage with macroeconomic or crop models. This integration would allow for the evaluation of climate change impacts on crop yields (using crop models) and prices (using macroeconomic models). Multi-model ensembles of global gridded crop models are available in ISIMIP (2023) and could be coupled following a similar procedure to the one described here for the natural water systems or GHMs, while the integration of macroeconomic models such as computable general equilibrium (CGE) models (Hertel and Liu, 2016) into water system research has already been done (Parrado et al., 2020; Pérez-Blanco et al., 2021a; Pérez-Blanco and Gutiérrez-Martín, 2017; Ronneberger et al., 2009). By adding these and other new system modules, uncertainty could further cascade across systems. This can help us identify new vulnerabilities and further underpin robust decision-making.

On the other hand, as the number of modules, protocols, structures, and other modelling factors (inputs, parameters, structures) considered in the analysis grows, other issues may arise that may reduce the tractability of the problem. These issues are dealt with in our last three recommendations for improvement.

Fourthly, having incorporated multiple uncertainties, the model output may vary "so wildly as to be of no practical use" (Saltelli et al., 2008). However, as noted by Saltelli et al. (2008) and in line with previous work by Beven and Binley (1992) and Beven and Freer (2001) that introduced the equifinality concept (i.e. distinct configurations of model components such as inputs, parameters, or structures can lead to similar or equally acceptable representations of the real-world process of interest), this "trade-off may not be as dramatic as one might expect, and increasing the number of input factors does not necessarily lead to an increased variance in model output." (Beven and Freer, 2001). Typically, a few inputs create almost all the uncertainty, and the majority make a marginal contribution.

Fifthly, computational costs may pose a challenge to conducting uncertainty quantification and analyses, where (1) each model run demands a considerable amount of time stretching from minutes to hours or even longer (especially in the case of highly intricate models) and/or (2) the model encompasses numerous uncertain inputs, which expand the computational cost exponentially with the increase in the number of inputs – a phenomenon known as the curse of dimensionality. Addressing computational expenses is crucial in many practical sensitivity analyses and model intercomparison projects. Strategies to mitigate this burden include employing emulators or meta-models driven by machine learning techniques that are particularly suitable for large models (Storlie et al., 2009) and employing screening methods to reduce the dimensionality of the problem, e.g. high-dimensional model representations (Li et al., 2006).

Sixthly, at some point, modellers must decide on the boundaries for the uncertainty quantification, i.e. the inputs and models, which will condition the outputs of the modelling exercise. This involves defining some limits to not generate computational costs we cannot afford through model selection and other techniques. For example, techniques for model selection can be employed to assign weights to the models in the ensemble based on their performance in calibration and forecasting errors. This could help us not only reduce computational costs (e.g. by discarding some models) but also reduce potential biases, such as the simulation outputs from GHM MPI-HM, which yields discharge forecasts that are markedly lower than the other models (with reductions close to or equal to 100 %), shifting the ensemble spread downwards and with important implications for human system forecasting (see Fig. 5). It should be noted that, while model selection techniques based on forecasting errors can be implemented for GHMs and GCMs, the measurement of forecasting errors in human system models is significantly more challenging: information on agent crop choices in the DRB has only been available since 2004, which leads to a significantly more reduced data series that complicates the implementation of rolling origins or other techniques to measure forecasting errors. On the other hand, the adoption of model selection techniques on the basis of calibration errors can be misleading, since models with higher calibration errors may show better predictive performance (Pindyck, 2015).

The convenience of adopting model selection techniques is a question for debate, since weighting can significantly affect modelling results and condition stakeholder choices and decision-making. On the other hand, it has been contended that, whenever model selection techniques are not considered, each potential simulation outcome is equally important, "which can also be interpreted as an implicitly equal weighting" (Taner et al., 2019). This is more so the case when results are explicitly reported using best estimates as done in Figs. 3–5. While this statistical treatment is a key step in making results understandable to users, it may introduce non-trivial biases through the processing and communication of modelling results, which has to be explicitly addressed by the use of dispersion measures (Fig. 5) and by the development of adequate processing techniques for modelling outputs (e.g. serious games that convey the economic and environmental repercussions of water extremes). On the other hand, a similar critique can be made of weighting. The decision whether to assign weights to simulation outcomes or leave them open for interpretation remains a subject of debate among academics (Taner et al., 2019).

Appendix A: New infrastructures in the Douro River Basin Plan

Table A1. All new developments proposed in the Douro River Basin Plan.

AWDU	System	Situation	Scenario 1	Scenario 2	Scenario 3
2000003	Esla	Irrigation modernization	×	×	
2000006	Esla	Irrigation modernization	×	×	
2000014	Órbigo	Irrigation modernization	×	×	
		La Rial and Los Morales reservoirs	×	×	×
2000017	Órbigo	Irrigation modernization	×	×	
		La Rial and Los Morales reservoirs	×	×	×
2000018	Órbigo	Irrigation modernization	×	×	
		La Rial and Los Morales reservoirs	×	×	×
2000023	Órbigo	Irrigation modernization	×	×	
		La Rial and Los Morales reservoirs	×	×	×
2000025	Tera	Irrigation modernization	×	×	
2000026	Tera	Decrease in irrigated areas	×	×	×
2000034	Esla	Expansion of irrigated areas	×		
2000038	Órbigo	Irrigation modernization	×	×	
		La Rial and Los Morales reservoirs	×	×	×
2000041	Esla	New AWDU in 2027	×	×	×
		Balsa Sector IV reservoir to AWDU 2000033	×	×	×
2000047	Esla	Expansion of irrigated areas	×		
2000049	Tera	New AWDU in 2027	×	×	×
		Expansion of irrigated areas to AWDU 2000025	×		
2000052	Órbigo	Irrigation modernization	×	×	
		La Rial and Los Morales reservoirs	×	×	×
2000054	Esla	New AWDU in 2033	×	×	×
		Valcuende de Almanza reservoir to AWDU 2000040	×	×	×
2000055	Esla	Expansion of irrigated areas	×		
		Vallehondo reservoir	×	×	×
2000057	Esla	Expansion of irrigated areas	×		
2000064	Carrión	Irrigation modernization	×	×	
		La Cueza 1 and La Cueza 2 reservoirs	×	×	×
2000065	Carrión	Irrigation modernization	×	×	
		La Cueza 1 and La Cueza 2 reservoirs	×	×	×
2000071	Pisuerga	Expansion of irrigated areas	×		
		Burejo reservoir	×	×	×
2000073	Pisuerga	Expansion of irrigated areas	×		
		Las Cuevas reservoir	×	×	×
2000080	Arlanza	Expansion of irrigated areas	×		
		Irrigation modernization	×	×	
		Castrovido reservoir	×	×	×
2000082	Carrión	Irrigation modernization	×	×	
		La Cueza 1 and La Cueza 2 reservoirs	×	×	×
2000083	Carrión	Irrigation modernization	×	×	
		La Cueza 1 and La Cueza 2 reservoirs	×	×	×
2000091	Bajo Duero	Irrigation modernization	×	×	
2000092	Bajo Duero	Irrigation modernization	×	×	
2000094	Bajo Duero	Irrigation modernization	×	×	

Table A1. Continued.

AWDU	System	Situation	Scenario 1	Scenario 2	Scenario 3
2000097	Carrión	Expansion of irrigated areas	×		
		La Cueza 1 and La Cueza 2 reservoirs	×	×	×
2000100	Pisuerga	Expansion of irrigated	×		
		Boedo reservoir	×	×	×
2000102	Pisuerga	Valles de Cerrato reservoir	×	×	×
2000108	Bajo Duero	Irrigation modernization	×	×	
2000122	Alto Duero	Irrigation modernization	×	×	
2000128	Alto Duero	Expansion of irrigated areas	×		
		Irrigation modernization	×	×	
2000132	Alto Duero	Expansion of irrigated areas	×		
		Dor reservoir	×	×	×
2000143	Alto Duero	Expansion of irrigated areas	×		
2000166	Cega-Eresma-Adaja	New AWDU in 2033	×	×	×
		Torreiglesias reservoir to AWDU 2000159	×	×	×
2000168	Cega-Eresma-Adaja	Expansion of irrigated areas	×		
		Lastras de Cuéllar reservoir	×	×	×
2000171	Cega-Eresma-Adaja	New AWDU in 2033	×	×	×
		Carbonero, Cigueñuela, Lastras de Cuéllar, and Torreiglesias reservoirs to AWDUs 2000168 and 2000164	×	×	×
2000202	Águeda	Irrigation modernization	×	×	
2000207	Tormes	New AWDU in 2027	×	×	×
		Expansion of irrigated areas to AWDU 2000208	×		
2000209	Tormes	Expansion of irrigated areas	×		
		Gamo reservoir	×	×	×
2000210	Tormes	Expansion of irrigated areas	×		
		Margañán reservoir	×	×	×
2000211	Tormes	Decrease in irrigated areas	×	×	×
2000212	Águeda	New AWDU in 2027	×	×	×
		Expansion of irrigated areas to AWDU 2000185	×		
2000213	Esla	New AWDU in 2027	×	×	×
		Expansion of irrigated areas to AWDU 2000202	×		
2000280	Órbigo	Expansion of irrigated areas	×		
		Irrigation modernization	×	×	
2000282	Esla	New AWDU in 2033	×	×	×
		Balsa Sector V reservoir to 2000033	×	×	×
2000598	Órbigo	Irrigation modernization	×	×	
		La Rial and Los Morales reservoirs	×	×	×
2000600	Órbigo	Irrigation modernization	×	×	
		La Rial and Los Morales reservoirs	×	×	×
2000605	Cega-Eresma-Adaja	New AWDU in 2033	×	×	×
		Carbonero, Cigueñuela, Lastras de Cuéllar, and Torreiglesias reservoirs to AWDU 2000164	×	×	×
2000606	Cega-Eresma-Adaja	New AWDU in 2033	×	×	×
		Torreiglesias reservoir to AWDU 2000159	×	×	×
2000607	Cega-Eresma-Adaja	New AWDU in 2033	×	×	×
		Lastras de Cuéllar reservoir to AWDU 2000168	×	×	×
2000608	Cega-Eresma-Adaja	New AWDU in 2033	×	×	×
		Carbonero and Ciguiñuela reservoirs to AWDU 2000164	×	×	×

Appendix B: Spatial distribution of profit and employment for each ensemble model

Figure B1. Spatially disaggregated impacts (best estimates) of discharge anomalies under climate change (**a** RCP2.6, **b** RCP6.0, **(c)** RCP8.5) on profit in the AWDUs of the Douro River basin for the 2006–2040 and 2040–2070 periods. Changes in profit are obtained as the difference between simulated values under alternative climate change and management scenarios and observed values in the year 2017. It is important to note that the GHM MPI-HM yields discharge forecasts that are markedly lower than those obtained with the other models, leading to outliers in the employment and profit predictions, which decrease by nearly 100 % in most of the years in the series. This outlier is excluded from the best estimates reported in this figure.

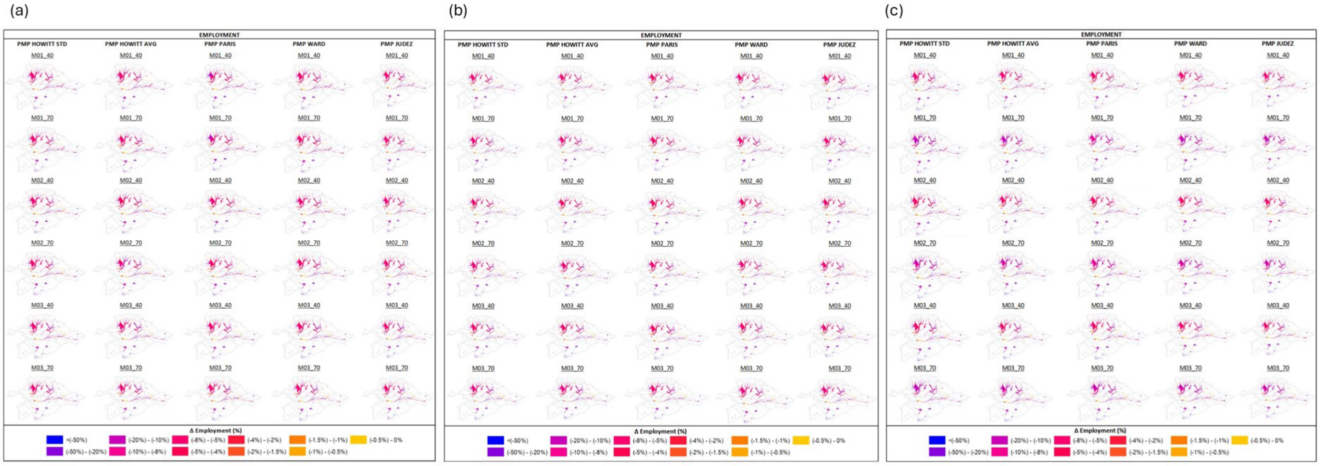

Figure B2. Spatially disaggregated impacts (best estimates) of discharge anomalies under climate change (**a** RCP2.6, **b** RCP6.0, **c** RCP8.5) on employment in the AWDUs of the Douro River basin for the 2006–2040 and 2040–2070 periods. Changes in employment are obtained as the difference between simulated values under alternative climate change and management scenarios and observed values in the year 2017. It is important to note that the GHM MPI-HM yields discharge forecasts that are markedly lower than those obtained with the other models, leading to outliers in the employment and profit predictions, which decrease by nearly 100 % in most of the years in the series. This outlier is excluded from the best estimates reported in this figure.

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

Supplement. Supplement 1 contains data input of the PMP models (see Excel file "Table S1" attached to the submission for the database). Supplement 2: data of water allocations for each AWDU (see Excel file "Table S2" attached to the submission. Two sheets – first: monthly allocation, second: yearly water allocation deficit; input for the micro-model) Supplement 3: data of the impacts on profit and employment for the AWDUs (see Excel file "Table S3" attached to the submission) The supplement related to this article is available online at: https://doi.org/10.5194/hess-28-4501-2024-supplement.

Author contributions. LGG: data curation, formal analysis, software, investigation, visualization, writing – original draft, writing – review and editing. NMML: data curation, software, investigation, writing – review and editing. CGM: supervision, software, investigation, writing – review and editing. ÁSD: data curation, software. PSS: data curation, software. JMPM: data curation, writing – review and editing. JP: writing – review and editing. CDPB: conceptualization, funding acquisition, project administration, supervision, investigation, methodology, resources, writing – original draft, writing – review and editing.

Competing interests. The contact author has declared that none of the authors has any competing interests.

Special issue statement. This article is part of the special issue "Drought, society, and ecosystems (NHESS/BG/GC/HESS inter-journal SI)". It is not associated with a conference.

Financial support. This research is part of project no. TED2021-131066B-I00 funded by MCIN/AEI/10.13039/501100011033, by the European Union "NextGenerationEU"/PRTR, by project WADECO (PID2023-146274OB-I00) and by the PRIMA Foundation's TALANOA-WATER project (Talanoa Water dialogue for Transformational Adaptation to Water Scarcity under Climate Change).

Review statement. This paper was edited by Giuliano Di Baldassarre and reviewed by Adam Loch and one anonymous referee.

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