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A review of economic calibrated mathematical programming models for agricultural water reallocation

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ABSTRACT

This study presents a bibliometric and systematic review of economic calibrated mathematical programming models for agricultural water reallocation. Our analysis describes trends and emerging directions in research, identifies major scientific challenges, and discusses related advances and research gaps. Key challenges and research gaps emerging from our review include lack of model (particularly of forecasting errors) and data (particularly water use data) validation, insufficient uncertainty quantification, issues of model performance beyond the calibration range, and uncoordinated coupling (and other) experiments with limited impact. We diagnose research gaps and identify key drivers, explore promising research avenues with the potential to address them, and provide a synthetic list of recommendations with potential of significantly advancing the state of the art.

1. Introduction

Water has multiple uses, including basic human needs (e.g., supporting health and the environment) and economic uses for food, energy, manufactures, and services provision (United Nations, 2021). The widening gap between an increasing water demand (due to population growth and changing living standards) and a decreasing supply (due to climate change), aggravated by inflation, mass migration, pandemics, and other crises, is amplifying the trade-offs among alternative and increasingly competing uses of water, and constraining decision makers to reallocate available resources towards strategic uses that enhance welfare (Joseph et al., 2024). Most of these reallocations originate in the agricultural sector, because of two reasons: *first,* agriculture is the largest water user worldwide, representing 70 % of the global freshwater withdrawals (United Nations, 2024); *second*, agriculture typically concentrates the marginal uses of the resource, i.e., those that generate the least value added (e.g., EUR of income or number of jobs created per m^3), and therefore offers the greatest potential for enhancing economic output (via water reallocations) and welfare (provided a suitable level of income redistribution) (United Nations, 2024).

Economic models help us understand, forecast, and manage the behavior of agricultural water users, as well as their ecological and socioeconomic impacts, and thus are instrumental to inform and design water reallocations (UNDRR, 2019, 2021). Economics methods to model the behavior of agricultural water users include econometrics (Basnet et al., 2021), mathematical programming (Sapino et al., 2023), behavioral economics (Mesa-Vázquez et al., 2021), Agent Based Models (Huang et al., 2016), Data Envelopment Analysis (Kouriati et al., 2023), survey-based methods (e.g., contingent valuation) (McGurk et al., 2020), and field experiments, of which the most frequently used are Mathematical Programming Models (henceforth, MPMs) (Graveline, 2016b). MPMs build upon the fundamentals of microeconomics theory, assuming rational and utility maximizing individuals with stable, complete, and transitive preferences that can be represented in a utility function (Chilaka et al., 2024; Graveline, 2016; Heckelei et al., 2012). MPMs leverage observed data to reproduce real life agricultural water users and agricultural production systems, and test whether simulated responses align with what theory predicts, thus deepening our understanding of the link between human behavior, water use, and policy. Two major strands of MPMs can be distinguished: normative, which aim to identify optimal water resources allocations based on *a priori* assumptions by the modeler (e.g., "what decision should farmers take to maximize profit?"); and positive or calibrated, which aim to calibrate a model that can reproduce the observed behavior of agricultural water

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users (i.e., “what is the rationale behind farmers’ choices?“), and forecast their responses to *stimuli* (Sapino et al., 2020). This study reviews and critically discusses the evolution of *calibrated* MPMs of agricultural water users over the past decade, following up on the last available review by Graveline (2016).

The paper is structured as follows. Section 1.1 presents the basic form of a MPM and briefly discusses its key features, while Section 1.2 summarizes the key challenges in the calibrated MPM literature that were identified by Graveline (2016) a decade ago. Section 2 presents the methods used for our bibliometric and systematic review of MPMs over the past 10 years (2015–2024), while Section 3 and Section 4 categorically present and discuss the results of the bibliometric and systematic review, respectively. Section 5 concludes the paper and provides a list of recommendations for future research.

1.1. Calibrated MPMs

MPMs represent the behavior of an economic agents at spatial scales that range from an individual farmer to clusters of them (e.g., an irrigation/agricultural district). In a typical MPM, the economic agent can decide on land and water use, technology adoption, and capital investments, to maximize his/her utility subject to a domain conformed by a set of constraints (such as water availability or agronomic constraints). The basic and static form of a MPM can be represented as follows:

$$\max_{x} U(x) = U(z_1(x);\ z_2(x); z_3(x) \dots z_m(x)) \tag{1}$$

$$\text{s.t.}: 0 \le x_{i,j} \tag{2}$$

$$\sum_i x_{i,j} \le b_j \tag{3}$$

$x \in R^n$ is the input portfolio, which consists of a matrix representing the land, water, technology, capital and other relevant inputs *j* allocated to the production of the crop *i*, where the amount of input *j* allocated to the crop *i* can be represented by $x_{i,j}$. U(X) is the utility function, which can be driven solely by profit (z_1, *single-attribute*), but also by other potentially relevant attributes such as risk avoidance or management complexity avoidance (z_2, …, z_m, *multi-attribute*). The utility function can adopt multiple forms, such as Cobb-Douglas, linear, or quadratic, among others, and can be calibrated using a wide array of techniques (Sapino et al., 2020).

Positive MPMs can be broadly classified into three families, which reflect on the key modeling features discussed above: Linear Programming (LP) models, Positive Mathematical Programming (PMP) models, and Positive Multi-Attribute Utility Programming (PMAUP) models (Graveline, 2016; Sapino et al., 2020).

LP modeling is a method for the optimization of a linear objective function subject to linear constraints. In positive LP models, the linear objective function is calibrated to observed choices, which can be done using a wide variety of methods that typically yield information on calibration errors. One such method is to calibrate the objective function using an external econometric model, with the option of subsequently adjusting the resultant parameter values to feasible parameter values within the domain of the LP model (Galko and Jayet, 2011). Another method to calibrate LP models is to increase the degrees of freedom by incorporating additional attributes, such as risk aversion (multi-attribute LP). For example, the Minimization of Total Absolute Deviation (MOTAD) approach calibrates a risk aversion parameter by minimizing the distance between a modeled baseline and observations (Hazell, 1971). Another method to calibrate multi-attribute LP is to define the objective function as a function of weighted attributes, where weights are calibrated to minimize the distance between simulations and observations, as in the Weighted Goals Programming (WGP) approach (Sumpsi et al., 1997).

The key advantage of LP is its low computational cost as compared to alternative calibrated MP, which has made it possible for LP models to operate at a high granularity farm level (Jayet et al., 2023). A disadvantage is that LP models often lead to unrealistic corner solutions, where the agent chooses the crop with the highest profit until a constraint is binding, and then jumps to the second-best crop. To address this caveat, scientific literature has developed more sophisticated LP models such as the cross-mix approach (McCarl, 1982), which adds an *ad-hoc* constraint to ensure a convex combination of historical crop mixes. This method nonetheless prevents agents from choosing crop portfolios that have not been observed, leading to “overly constrained” results that call for further *ad-hoc* components such as the addition of “synthetic” crop portfolios to the feasible set, which are nonetheless based on heuristics rather than the result of a mechanistic model simulation (Chen and Önal, 2012; Graveline et al., 2014).

PMP modeling is “an intermediate” between mathematical programmers’ deductive approaches and the inductive approach of econometric-based methods, and is arguably the most widely used MPM to study the behavior of farmers (Graveline et al., 2014). PMP features a non-linear objective function that avoids corner or other unrealistic solutions and perfectly replicates observed agent behavior (i.e., the calibration error is zero). Such objective function is calibrated using “information contained in dual variables of calibration constraints, which bound the solution of the original linear programming problem to observed activity levels” to “specify a non-linear objective function such that observed activity levels are reproduced by the optimal solution of the new programming problem without bounds” (Heckelei and Britz, 2005). The non-linear form of the objective function is typically obtained by adding an *ad-hoc* non-linear cost or yield function whose calibration results mimic observed choices without error. Several methods to calibrate the parameters of the non-linear cost or yield functions exist, including the original approach that relied on a yield function (Howitt, 1995), as well as several methods relying on a cost function (Dagnino and Ward, 2012; Júdez et al., 2002). The major criticism to PMP models is the difficulty to find an “economic or technological rationale” for this *ad-hoc* non-linear component in the objective function, “despite several attempts” (Heckelei et al., 2012); albeit it is worth noting the use of a mean-variance risk analysis where the non-linear component can be rationalized by the covariance matrix (Cortignani and Severini, 2009). This difficulty can be seen as a logical consequence of the nature and design of PMP models, which were created for modelers who, “for lack of an empirical justification, data availability, or cost, find that the empirical constraint set does not reproduce the base-year results”, i.e., as a method to bypass data or conceptual problems towards reproducing observed choices (Howitt, 1995).

PMAUP models build on portfolio theory to create a multi-attribute objective function that aligns with a finite set of observed choices, yields, costs, and prices (Gutierrez-Martin and Gomez, 2011). The utility function can adopt alternative nonlinear forms (although a Cobb-Douglas function is typically used due to its flexibility), where its parameters assign weights to the competing attributes of the function (e.g., profit maximization v. risk minimization). Instead of using dual variables for calibration as in PMP, PMAUP models use numerical methods to build a production possibility frontier representing the optimal combinations of attributes within the feasible set (i.e., the maximum profit that can be achieved for a given value of risk, or alternatively the maximum risk that can be avoided for a given value of profit–all within the domain), and then identify the parameter values that make the objective function tangent to the point of the production possibility frontier that matches the observed choices by the agent. This method aligns with the fundamentals of microeconomic theory and has a sound economic rationale; however, like LP, PMAUP leads to calibration errors that may be nontrivial, especially where significant conceptual (e.g., a relevant attribute cannot be measured or is not included in the problem definition), or data gaps exist and the observed crop portfolio is distant from the production possibility frontier. Moreover, "calibration of PMAUP models is challenging where there is a large number of choice variables (several alternatives in the crop portfolio) and cross-sectional variation is low (time-series variation might be confounded with other trends)", since this can lead to "instability in the model calibration that is difficult to rationalize (e.g. abrupt changes in parameter values following the introduction of an additional attribute)" (Sapino et al., 2020).

1.2. State of the art of MPMs in 2016

Several literature reviews on calibrated MPMs are available in the literature. Heckelei & Britz (2005) survey PMP models with a focus on assessing the empirical improvements in calibration practices. Frahan et al. (2007) identify the most relevant critiques to PMP models at the time and present the key developments in the field that in their view have addressed or can contribute to address these critiques. Heckelei et al. (2012) present methodological and calibration advances in the PMP literature, critically reflect on the lack of "technological or economic rationale" in PMP models, and identify promising approaches to address this major challenge. The most recent literature review of calibrated MPMs of agricultural water users is that of Graveline (2016), which takes stock on previous reviews and further expands their analysis. Albeit using a more systematic approach to data analysis, the literature review adopts, like that of its predecessors, an heuristic/expert judgement approach for the bibliographic search, which results in a selection of MPMs that is biased towards PMP (which admittedly is the most relevant of MPMs) and LP, while treating in a limited way general multi-attribute theory and PMAUP, whose employment in the area of agricultural water reallocations was emerging at the time. Building on the above-mentioned precedent reviews and her own systematic review on the topic, Graveline (2016) identified six key challenges to the MPMs research community, namely: 1) validation, 2) incorporation of water inputs, 3) incorporation of risk in the objective function, 4) incorporation of uncertainty, 5) spatial detail, 6) adoption of new technologies and practices, and 7) far from reference simulations. For each challenge, the author highlighted relevant advances and gaps, which are reported in Table 1.

2. Methods

Existing reviews of MPMs for agricultural water reallocation rely on heuristics/expert knowledge for bibliographic search and data extraction and analysis rather than adopting a more systematic approach (Graveline, 2016; Heckelei et al., 2012). This has led to biases such as the exclusion of PMAUP or LP models. In this study, we adopt a systematic and structured methodology to our literature review, articulated in two parts: i) search criteria and data extraction and ii) data analysis. The search criteria and data extraction methodology adopts the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) approach and is presented in Section 2.1. The data analysis methodology comprises two distinct parts: Bibliometric review methods presented in Section 2.2; and Systematic review methods presented in Section 2.3.

2.1. Search criteria and data extraction

The search criteria and data extraction procedure adopted in this review follows the PRISMA approach, comprising the following steps: (i) research questions, (ii) sources of information, (iii) searching strategy, (iv) eligibility criteria, (v) risk of bias, and (vi) data extraction (Page et al., 2021). Below we present how this workflow was implemented in our review of calibrated MPMs for agricultural water reallocation.

i) **Research question**: We aim at tracking progress (advances and persisting/emerging gaps) in the challenges identified in the review by Graveline (2016), as well as identifying novel challenges

Table 1
Research challenges in MPMs and related advances and gaps as of 2016 (adapted from Graveline, 2016).

Challenge	Relevant advances	Research gaps
Validation	Some ex-post validation of MPMs conducted through experiments (Blanco et al., 2008; Gocht, 2005; Heckelei and Britz, 2000; Kanellopoulos et al., 2010) suggest a protocol for model validation, with limited application.	Validations of MPMs are still rare. The few publications that validate the forecasting capability of MPMs in the literature focus on ex-post experiments, ignoring other approaches like 'out-of-sample' testing typically adopted in other economic models (e.g., econometrics) and the ecological modeling community.
Incorporation of water inputs	Multiple techniques available: - Discrete points that represent yield responses to different levels of input application (Cortignani and Severini, 2009; Graveline et al., 2012; Taylor and Young, 1995). - Integration of production functions in PMP using a quadratic yield-input function (Cai and Wang, 2006; J. Connor et al., 2009; J. D. Connor et al., 2012, p. 201; R. Howitt et al., 2001). - Use of CES yield-input functions in PMP (Howitt, 1995) - Integration of agronomic production functions into otherwise LP (J. Connor et al., 2009; Dinar et al., 1991; Posnikoff and Knapp, 1996; Weinberg and Kling, 1996). - Integration of agronomic production functions into PMP using CES (Frisvold and Konyar, 2012; R. E. Howitt, 1995; Medellin-Azuara et al., 2010; Merel et al., 2011) or nested CES (Frisvold and Konyar, 2012; Medellín-Azuara et al., 2012). - Calibration of model to agronomic data (Merel et al., 2014). - Calibrate the CES model against observed agronomic input-yield response curves (Graveline and Mérel, 2014; Merel et al., 2014)	- Most models still allocate water, and other relevant inputs, in fixed proportion to land - The rationale for choosing quadratic yield-input functions is not supported by agronomic research (it does not fit the agronomic plateau) (Graveline, 2016), and in the case of two inputs may allow for too much substitution (Knapp and Schwabe, 2008). - CES function allows for limited input substitution and is closer to the agronomic plateau; but does not decrease after a certain threshold which is necessary to represent loss of yield due to waterlogging. - Integration of production function into LP does not allow for economies of scale (increasing acreage has no impact on yields). This is resolved by PMP models integrating agronomic production functions, but this assumes the same substitution among different types of inputs. - Nested CES functions can provide different substitution elasticities for different inputs, but like the preceding PMP models they do not calibrate the CES function to agronomic functions. This is addressed by PMP models calibrated to the agronomic function by adding an extra adjustment cost term to increase the degrees of freedom.
Incorporation of risk in objective function	- Risk incorporated implicitly rather than as an additional attribute in PMP through Constant (CARA) or Decreasing Absolute Risk Aversion (DARA) (Arata et al., 2014; Petsakos and Rozakis, 2011). - Risk incorporated as attribute in multi-attribute LP models such as MOTAD (Hazell and Norton, 1987),	- PMP water reallocation models do not account for risk. Advances towards the incorporation of risk in the objective function have been adopted in PMP applications other than water.

(continued on next page)

Table 1 (*continued*)

Challenge	Relevant advances	Research gaps
	which adds one more degree of freedom that is useful for calibration. [Albeit not reported in the original Graveline (2016) review, risk had been also added explicitly in PMAUP at the time (see, e.g., Gutierrez-Martin & Gomez (2011)]	
Incorporation of uncertainty	Probabilistic risk and input uncertainty are incorporated using scenario-based approaches, notably discrete stochastic programming models where the decision problem is done in several stages (e.g., different periods of the year) in which new information is available (e.g., water available). Constraints link periods with each other (e.g., capital investments in first stage remain over time) (Calatrava and Garrido, 2005; Dono et al., 2013; McCarl et al., 1999; Rae, 1971a, 1971b)	- Sensitivity analysis to quantify input uncertainties is local and limited to scenario-based/one-at-a-time (OAT) approaches (e.g., simulating the impact of alternative water pricing policies). Global Sensitivity Analyses not reported in the literature. - Parameter uncertainties within models are ignored. - Structural uncertainties within models are ignored. Multi-model ensembles are not reported in the literature.
Spatial detail	- Regional scale modeling has been adopted to explore the social optimum of a region and in homogeneous areas (large farm assumption), which reduces computational costs and data requirements. - Downscaling of regional modeling used to increase granularity (Cantelaube et al., 2012; Chakir, 2009; Gocht and Britz, 2011; R. Howitt and Reynaud, 2003).	- Scale conditions results, but the choice of model scales is rarely discussed. Farm-level modeling, which seems appropriate for representing the system, is often unfeasible due to lack of data and computational constraints. Regional modeling is inadequate for water where aggregation is large (e.g., freely reallocating water between different basins). - Downscaling does not account for farm-level conditions and constraints, such as water constraints or infrastructures.
Adoption of new technologies and practices	None besides yield-input functions (see challenge on incorporation of water inputs) [Albeit not mentioned in the original Graveline (2016) paper, Multi-Agent Cellular Automata (MACA) models applied to land use cover/land use change offer the possibility to couple a cellular component representing an environment/space with human agents representing decision-making to assess how social and spatial interactions among autonomous agents (e.g., irrigators) in an environment/space (e.g., the basin) affect the meso-scale (e.g., technology adoption) (Kremmydas et al., 2018). These models have been used for long (Berger, 2001), including for the study of water reallocations albeit typically relying on normative MP(Becu et al., 2003). MACA applications using calibrated MP existed pre-2016 (e.g., Morgan and Daigneault, 2015) use a PMP), but they did not address water-related aspects].	- Limited research on technology/practices adoption and adaptation processes at the micro, meso and macro scale. - Limited integration with meso and macro models.
Far from reference simulations	None	Empirical observations show that PMP and LP models often fail at predicting abrupt and unprecedented changes in behavior. Reasons for this limitation include: - Limited technical and economic data concerning transformational change (e.g., yield, costs, price, etc. of crops under climate change). - Where these changes have not been observed (and thus not used in the calibration), the non-linear component of the PMP model can penalize/prevent the adoption of better performing choices (i.e., the non-linear component may have different properties when remote from the baseline, such as non-constant first derivatives, which we cannot anticipate). - LP models at the farm scale often work with farm typologies that might evolve with time (expansion of farms, or evolution of technical constraints) and structural changes in typologies would require additional specifications to be included.

emerging in the scientific literature over 2015–2024 (and tracking related gaps and advances), to determine the current state of the art and identify research directions with high potential.

ii) **Sources of information**: The literature review leveraged scientific databases accessible through the platform Web of Science (WOS). This source was prioritized due to their extensive databases, precision, reliability, and recognition within the scholarly domain, as well as meta-data availability necessary for the bibliometric approach.

iii) **Searching Strategy:** Given the focal point of this study on calibrated MPMs of agricultural water users, search keywords were tailored around prominent models pertinent to this context, namely *"Linear"* (LP), *"Non-linear"*, *"Positive"* (PMP), *"Weighted Goal"* (WGP), and *"Multi-Attribute"* (PMAUP), which were complemented with the keywords *"mathemat*"*, *"program*"* and "*model*", where "*" is a wildcard allowing for any possible word ending. These modeling families formed the foundational basis of the search protocol. In this review, all bibliographic searches were performed using the Topic Search (TS) field, which queries the title, abstract, and keywords of each record. In a second filter, the search protocol selected, among the papers that met the requirements above, those that included the search keywords "*water**" or "*agric**" (also in title, abstract and/or keywords).

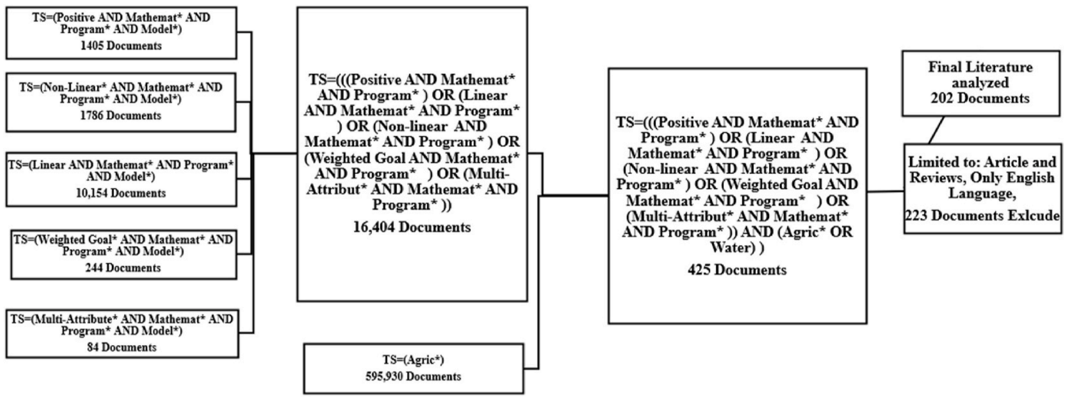

Fig. 1. Search Criteria with number of documents retrieved for each search (Retrieved in October 2024).

Fig. 1 presents the precise search strings employed in WOS database alongside the corresponding outcomes denoted by the number of publications retrieved. Applying this initial searching strategy yields 425 papers.

iv) **Eligibility Criteria:** To avoid redundancy in our analysis, we excluded conference proceedings, as these are frequently expanded and published as journal articles. Book chapters and other document types were also excluded due to limited accessibility. The results were further constrained to publications exclusively written in the English language and published between 2015 and 2024. Research areas that considered topics far from the objective of this paper were excluded (e.g., 'Tropical Medicine or Transportation'). This approach ensured the coherence and relevance of the selected literature with the pre-existing review from Graveline (2016). After applying this eligibility criteria, **223 publications** were marked as ineligible, reducing the number of papers in the sample to **202** (see Fig. 1). A final evaluation was carried out to assess relevance of the publications yielded by the abovementioned search criteria through an abstract screening (e.g. excluding publications using MPMs for agricultural supply chain or agri-industrial planning), which further constrained the final list by 83 publications, resulting in a final sample of **119 publications**.

v) **Risk of bias:** Despite these precautions to minimize selection and reporting bias through a transparent and collaborative screening process, we acknowledge that an inherent risk of source bias remains due to the use of bibliographic databases with differing coverage and indexing policies. As documented in recent comparative studies (Franceschini et al., 2016), no single database provides complete and perfectly accurate coverage of the scientific literature. Thus, it is possible that some relevant studies may not have been retrieved or fully indexed, and this limitation should be considered when interpreting the results of our review

vi) **Data Extraction:** For the *bibliometric review*, this step concerned the extraction of meta-data necessary for the methods presented in Section 2.2, such as name of the publication, year, author(s), title, abstract, cited references, etc. A complete list and description of the meta-data extracted for the bibliometric review is presented in the bibtex file available in Annex I. For the *systematic review*, data extraction was designed to gather information relevant to the research challenges and related advances and gaps. Initially, data on advances and gaps relevant to Graveline (2016) seven challenges (*validation, incorporation of water inputs, incorporation of risk, incorporation of uncertainty, spatial detail, adoption of new technologies and practices, far from reference simulations*), as well as related information on *modeling family (PMP, LP, PMAUP, other), methodology overview, case study region, results,* and *model innovations*, was collected. Building on this initial data extraction and the bibliometric review, authors surveyed trends in the literature and identified two additional relevant challenges emerging over the past decade not included in the original review by Graveline (2016), namely*, coupling processes* and *data validation*, for which we collected relevant data on research advances and gaps. A complete list and description of the data extracted for the systematic review is available in Annex I.

2.2. Data analysis: bibliometric review

The data analysis for the bibliometric review was performed using R 4.0.2 software (RStudio Team, 2023) and the open-source RStudio 'Bibliometrix' package developed by Aria & Cuccurullo (2017). The bibliometric review includes two parts: Descriptive analysis and Network analysis (Price, 1965).

2.2.1. Descriptive analysis

The *descriptive analysis* leverages the basic meta-data (author's name, number of citations, country, institution, journal) to identify annual publication trends and pinpoint seminal publications by number of citations, track author productivity, and identify the most relevant journals. Author productivity is assessed through the number of publications and the H-index (Hirsch, 2005), which adopts a value of h where the author has published at least h articles that have each been cited at least h times. Journal relevance is studied following the approach developed by Bradford (1934) which states that if journals in a specific field are ranked by number of articles into three groups, each group with about the same amount of articles, then the number of journals in each group should be proportional to $1{:}n{:}n^2$. If this is observed, the smaller group of journals ("core sources") holds a similar number of publications as the second and third group combined, and typically also concentrates the high-impact and seminal publications (Bradford, 1934).

2.2.2. Network analysis

The *network analysis* leverages the basic meta-data to identify the intellectual (how authors influence the community), conceptual (main themes and trends of scientific research) and social (how authors and institutions interact in the production of research) structures of the field (Verma and Gustafsson, 2020). Network analysis was implemented using three techniques: co-author, co-citation, and co-word analysis.

Co-author analysis is adopted to explore the social structure of the research field following the method developed by Peters and Raan (1991), who unravel the structure of collaboration networks within a field by considering the number of co-authored publications.

Co-citation analysis is a widely used bibliometric approach at author and document level that utilizes citation counts to gauge similarity among documents, authors, and journals (Nerur et al., 2008). The co-citation analysis measures the number of citations per paper as well as the relationship between two authors or documents, by counting how many times two publications are cited jointly by a third publication (Eom, 2008).

Co-word analysis technique is employed to explore the thematic profile of specific research domains (Callon et al., 1983). This approach involves the examination of key terms that encapsulate the core content of papers, with the assumption that co-occurring terms denote related concepts. The resultant semantic maps derived from co-word enable a depiction of the evolution and present state of the literature, thus offering insights into the cognitive structure of the field (Aparicio et al., 2019). Co-word analysis is carried out building a co-occurrence matrix based on the keywords for each of the selected publications, including Authors' keywords (i.e., those provided by the author(s) at the time of publication) and other alternative approaches such as Keywords Plus (i.e., words or phrases frequently appearing in references titles, but not the article itself). The resulting set of keywords is then divided into different clusters, which are positioned on a thematic map and divided into four quadrants following the concepts of Callon's Centrality and Density (Callon et al., 1991). Callon's centrality (x-axis) measures the degree of interactions of themes (or clusters) with other themes, where Clusters with strong connections to other clusters and themes can be considered 'central' and indicative of influential significance within the conceptual structure of a field. Callon's density (y-axis) measures the degree of interconnectedness of keywords present inside a cluster, by calculating the number of co-occurrences between the terms inside a cluster to the actual number of maximum possible connections. Density therefore measures how much a cluster of terms has been overall developed compared to other clusters.

2.3. Data analysis: systematic review

The systematic review leverages data reported in Annex I to categorically compare the state of the art in 2016 with that of 2024 for each challenge, identifying and discussing the most relevant research advances and gaps (Graveline, 2016). To assess trends in the seven challenges originally identified in Graveline (2016) (namely, *validation, incorporation of water inputs, incorporation of risk, incorporation of uncertainty, spatial detail, adoption of new technologies and practices, far from reference simulations*), we use her paper as a point of reference and compare the research advances and gaps summarized in Table 1 to the advances and gaps identified in the literature for the period 2015–2024 reported in Annex I. To assess how literature addresses the novel challenges identified in our study (namely*, coupling processes,* and *data validation*), we rely on the progress observed in our own literature review over 2015–2024.

However, while Graveline (2016) discussed the adoption of new technologies and practices, as well as the challenges of far from the calibration range analysis, as distinct aspects of mathematical programming model simulation, we take a more integrated approach. In this review, these themes are considered together under a broader section on data validation and data-related limitations. This reflects the understanding that the ability of models to simulate technological adoption or to perform reliably outside of observed conditions fundamentally depends on the availability, quality, and representativeness of input data. By addressing these topics within a unified framework, we highlight the central role of data uncertainty, measurement errors, and information gaps as one of the main drivers of models structural vulnerability—whether in the context of emerging technologies, transformative scenarios, or general calibration and validation challenges.

3. Bibliometric review

3.1. Descriptive analysis

Applying the search protocol in Section 2.1 yielded 119 different documents from 64 different journal sources. A total of 330 different authors with an average of 3.5 co-authors per publication were found. 133 individual models appear in the sample (note that some publications employ model ensembles), of which 82 are PMP (61,6 %), 37 LP (27,8 %), 12 PMAUP (9 %), and 2 (1,6 %) other non-linear programming models (1,5 %). A larger time series (1990–2024, using the same search criteria without abstract screening described in Section 2.1) than the one considered for the review (2015–2024) is used in Fig. 2 to represent the annual publication trends and highlight the growing number of articles focusing on MPMs for agricultural water reallocation. A total of 117 were retrieved for the time series 1990–2014. In the last 10 years of series (2015–2024) the average number of publications per year increased to almost 12 (11,9), compared to the previous 25 years (1990–2014) where the average publications per year retrieved was 4.68, representing an increase of 154 %.

Fig. 3 assesses journal relevance through Bradford's Law. The "core sources" include 8 journals that accumulate almost 34 % (41 out of 119) of the total publications, while the remaining 56 journals in the sample represent 66 % of the total publications (81 out of 119). The "core sources" in the field of economic calibrated MPMs for agricultural water reallocation are: Agricultural Water Management (12 publications), Journal of Cleaner Production (8), Australian Journal of Agricultural and Resource Economics (4), Science of the Total Environment (4), Water Resources Management (4), Agricultural Systems (3), Bio-Based and Applied Economics (3), Environment Development and Sustainability (3), Environmental Modelling & Software (3).

3.2. Network analysis

Fig. 4 presents the collaborative network that results from the metadata using co-author analysis. The 50 most important collaborations are plotted, removing the isolated authors. The wider the circle the greater the number of publications, with the filling colors being related to the cluster of collaborations authors pertain to. Results show that collaborations between authors are frequent (significantly more common than single authorship) and persistent in the field (collaborations typically occur more than once). A key takeaway from this co-author analysis is that collaborations by nationality and type of MPM (e.g., PMAUP authors do not collaborate with PMP authors) are the predominant drivers of co-authored literature.

Fig. 5 presents the results of the co-citation analysis, which identifies citation patterns and tracks those influential publications serving as a foundation of the field. A co-citation link between publications is created when the same two papers are cited in at least two different articles. The diameter of the circle in the figure is proportional to the number of citations received by that paper. The color of the circle is given based on the similarity of authors and thematic communities and is automatically generated by the bibliometric software. Two clear color patterns emerge from the co-citation analysis: the blue cluster includes publications that employ multi-attribute approaches (PMAUP, LP) and/or coupled (hydro-economic, agroeconomic, micro-macroeconomic) models integrating MPMs (see e.g. Parrado et al., 2019); while the red cluster includes mostly PMP models focusing on calibration methods or Common Agricultural Policy analysis. The dense area in the center of the red cluster comprises the seminal PMP model by Howitt (1995) and the early PMP review by (Heckelei et al., 2012), together with other influential work in the area (Cortignani and Severini, 2009; Frahan et al., 2007; Heckelei and Wolff, 2003; Paris and Howitt, 1998; Merel et al., 2011). The blue cluster appears more evenly spread, with Graveline (2016) review and the seminal works of the PMAUP by Gómez-Limón et al. (2016) and Gutierrez-Martin & Gomez (2011), appearing in the dense area. Like the co-author analysis, the co-citation analysis exposes a rift between Single and Multi-Attribute models.

Figs. 6 and 7 show the thematic profile of the field using co-word analysis. The figures use two types of keywords, namely Authors' keywords (Fig. 6) and Keywords Plus (Fig. 7), and cluster them based on the

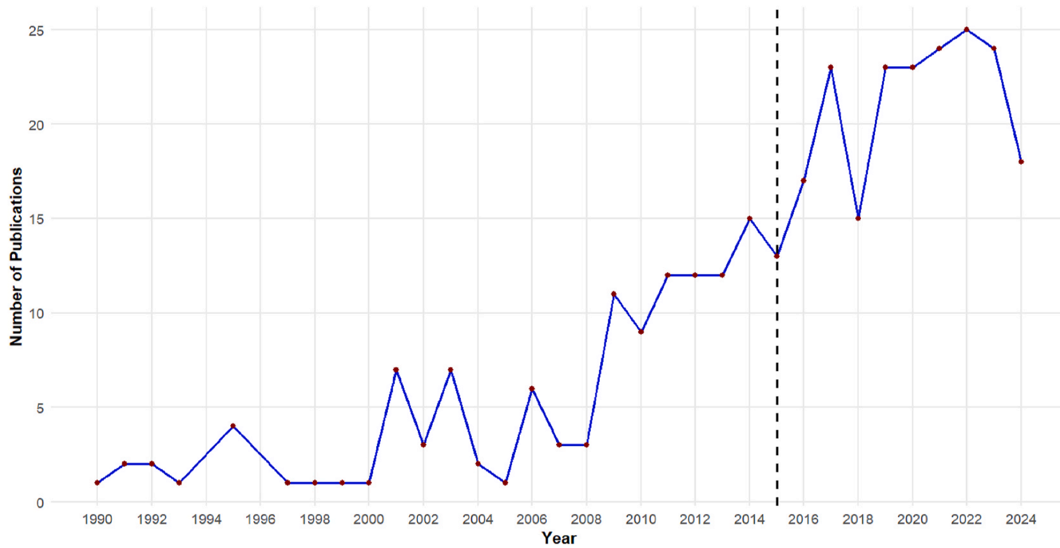

Fig. 2. Annual publication trends, 1990–2024.

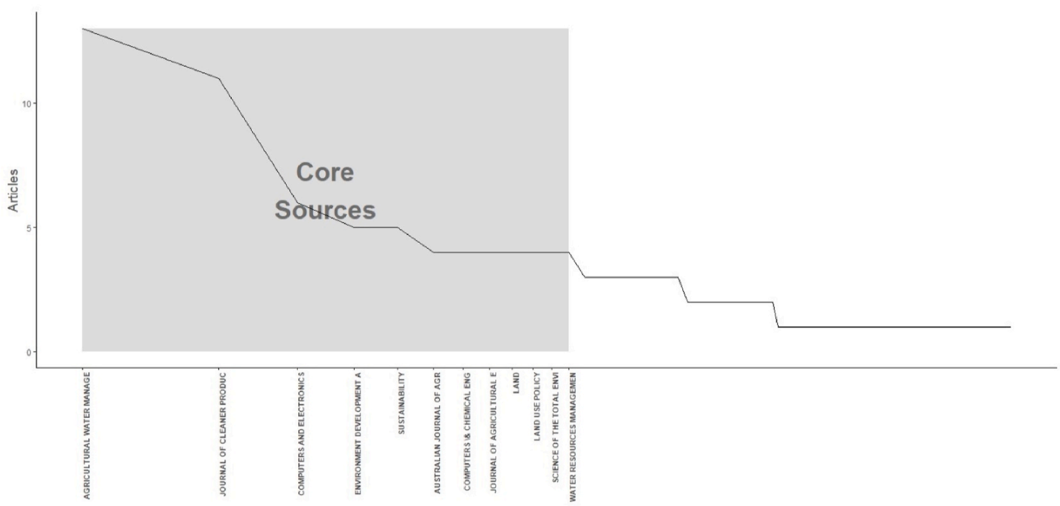

Fig. 3. Core sources by Bradford's law.

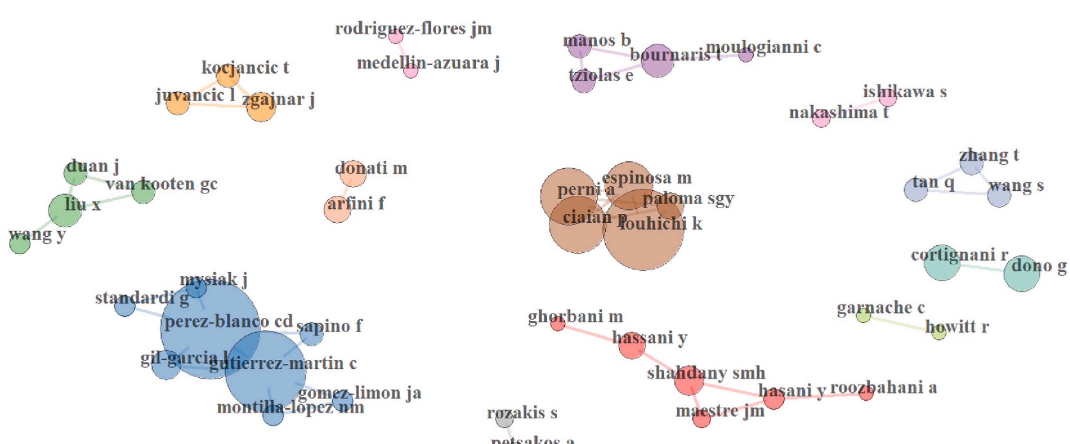

Fig. 4. Co-author analysis.

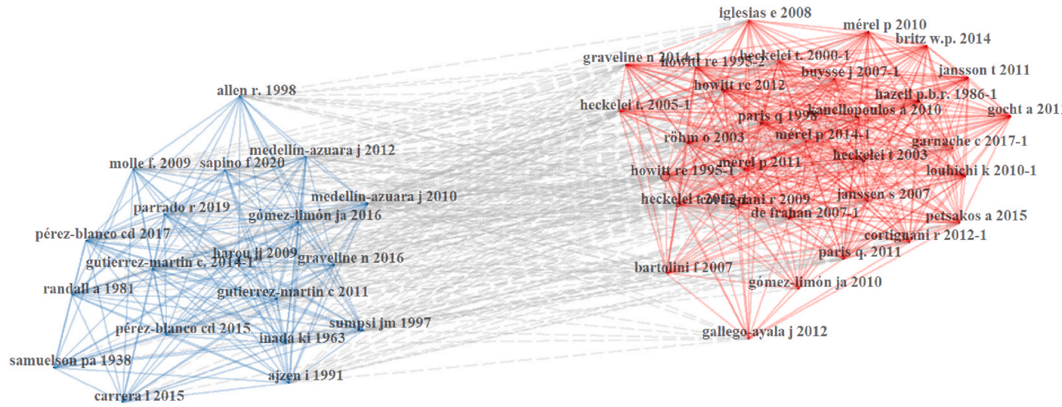

Fig. 5. Co-citation network.

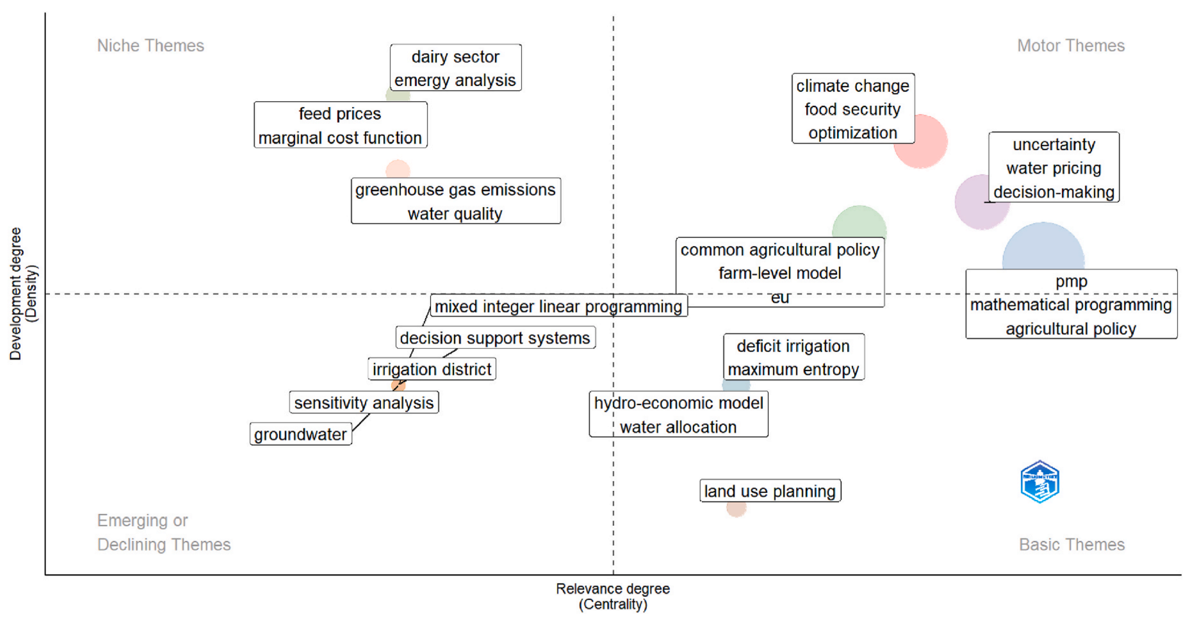

Fig. 6. Co-word keyword analysis (Authors' Keyword Level).

number of co-occurrences. We set the minimum level of co-occurrences for a word to be clustered at 5, where synonyms are treated as a single word (e.g. 'farm-level model' with 'farm level' or 'Common Agricultural Policy' with 'CAP'). The results are presented using the concepts of Callon's centrality (x-axis) and density (y-axis) (Callon et al., 1991). Following the Authors' keywords co-word analysis (Fig. 6), the four clusters with high centrality and density (or "motor themes") showed in the upper right corner of the figure are 'PMP', 'Uncertainty', 'Climate Change' and 'CAP'. Notably, the CAP cluster also includes the 'farm-level model' keyword, indicating that CAP ex-ante policy analysis is often performed at the farm level.

Following the Keywords Plus co-word analysis (Fig. 7), the motor themes also include 'Climate-Change' and 'Common Agricultural Policy'. A key difference compared to the Authors' keyword analysis is that 'Uncertainty' has a lower density, while water-related keywords have a higher density and now appear as motor themes (e.g., water, irrigation, aquifer, drought). Furthermore, model names in the Authors' Keyword co-word analysis ('PMP', 'LP') are replaced by their theoretical underpinnings (e.g., 'expected utility', 'revealed preference') or technical aspects (e.g., 'calibration', 'elicitation', 'maximum entropy') in the Keyword Plus co-word analysis.

Most of the seven key challenges for economic calibrated MPMs for agricultural water reallocation identified by Graveline (2016) (namely, validation, incorporation of water inputs, incorporation of risk, incorporation of uncertainty, spatial detail, adoption of new technologies and practices, far from reference simulations) can be observed in the thematic profile of the field in Figs. 6 and 7 —either directly ('uncertainty') or indirectly (e.g., 'evapotranspiration', 'irrigation', or 'water [use]' as part of incorporation of water inputs; 'farm-level model' and 'river-basin' as part of spatial scale; or 'ecosystem services' as part of adoption of new technologies and practices). The only challenges that do not directly or indirectly emerge from the co-word analysis are validation and far from reference simulations, which as we will show below are the challenges that have received less attention over the past decade in the literature, with significant research gaps persisting. The thematic profile of the field in Figs. 6 and 7 also highlights indirectly two additional challenges that were not included in Graveline (2016) review, namely, coupling processes (e.g.,'hydro-economic model'), and data validation (e.g., 'decision-making', 'maximum entropy'), which we incorporate to our analysis.

4. Systematic review

We articulate our systematic review across a total of nine challenges (validation, incorporation of water inputs, incorporation of risk, incorporation of uncertainty, spatial detail, adoption of new technologies and

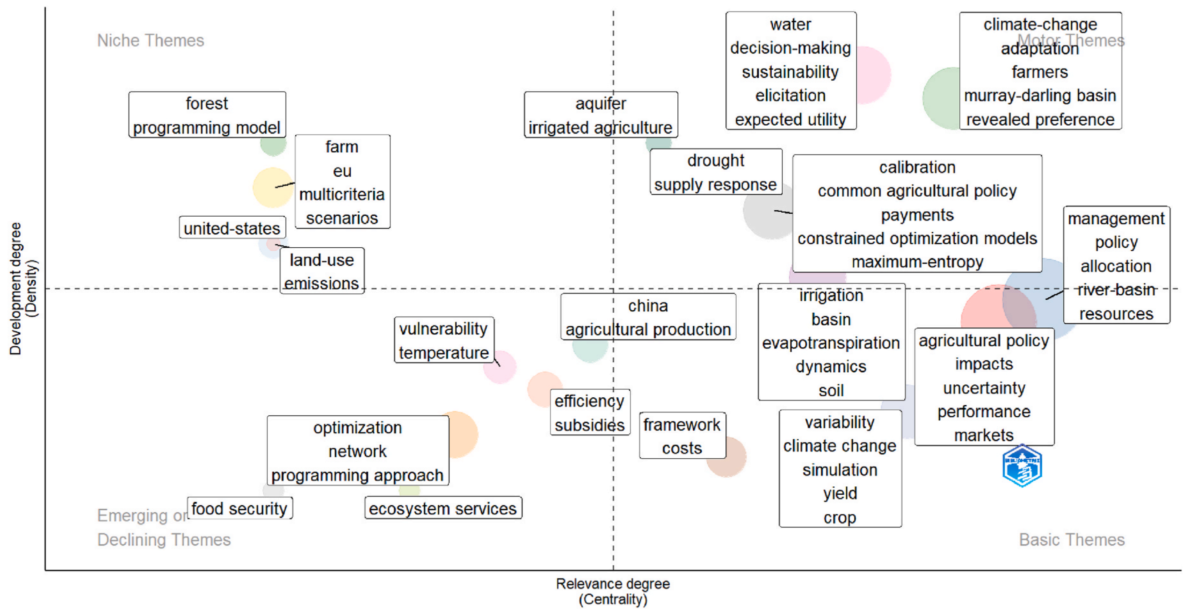

Fig. 7. Co-word keyword analysis (Keywords Plus Level).

practices, far from reference simulations, coupling processes, and data validation), for which we gather information on research advances and gaps. The relevance of each challenge across the sample is asymmetric: 4 publications address validation (ex-post), 22 incorporation of water inputs, 30 incorporation of risk, 24 Uncertainty, 118 spatial detail (through scale choice), 28 coupling processes, and 37 data validation (of which, 28 related to Adoption of new technology and 7 related to Far from reference simulations). The data gathered on research advances and gaps for each challenge, as well as the related information on modeling techniques, methodology, case study region, results, model innovations, and model objectives, is available in Annex I. The following sub-sections categorically compare the state of the art in 2015 to that of 2024 for each challenge and discuss advances and gaps.

4.1. Validation

Validation is an essential step in the development of predictive models like MPMs (Kanellopoulos et al., 2010), which encompasses the measurement and minimization of calibration (difference between observed and calibrated values) and forecasting errors (difference between model forecasts and out-of-sample data, i.e., observed data not included in the model calibration) (Sarris et al., 2020). Historically, MPMs have given significant attention to the measurement and minimization of calibration errors—in fact, the most widely used MPM, PMP, is designed to mimic the observed behavior of the farmer and thus take the calibration error to zero. A low or zero calibration error has been often used in MPMs' research as proof of validation, as noted by Cortignani & Dono (2020), who argue that MPMs can be "calibrated *and validated* by way [of a] positive approach" [emphasis added]. In this context, the measurement and minimization of forecasting errors has been widely disregarded in MPMs' research, as was already noted by Graveline (2016).

However, low calibration errors do not preclude forecasting errors, which can be high including for models with a calibration error of zero. This was already shown in the pioneering work of Heckelei & Britz (2000) and Blanco et al. (2008) who measure the forecasting errors of a set of PMP models by measuring deviations of model forecasts from observed data in the context of CAP reforms in France (Heckelei and Britz, 2000) and Italy (Blanco et al., 2008). Both studies measure forecasting errors using a fixed origin out-of-sample tests where fixed periods of the observed data sample are used for the calibration (holdout data, e.g., 1990–2014) and validation (out-of-sample data, e.g., 2015–2018). The authors report nontrivial forecasting errors, suggesting that their measurement should be integrated into MPMs' validation and selection. More recently, Garnache et al. (2017) argue that MPMs are a calibration tool and not a statistical estimation method and should be assessed as such, while Petsakos and Rozakis (2022) contend that the calibration error "does not seem to be a relevant criterion" for MPMs' validation, intercomparison and selection, particularly of PMP, and that "a more relevant interpretation of accuracy is that of *forecasting performance* [emphasis added]".

Yet, our 2015–2024 review finds no significant improvement in the measurement of forecasting errors compared to the pre-2016 situation: the majority of studies in our sample address calibration errors, with only 4 studies measuring forecasting errors (Mack et al., 2020; Maneta et al., 2020; Moulogianni and Bournaris, 2021; Schroeder et al., 2015). This suggests that model intercomparison, validation and selection is currently largely driven by the calibration error criterion, which depends on the estimation method adopted. Notably, a PMP designed to adjust a nonlinear parameter that yields a calibration error of zero will systematically outperform other calibration methods (although its forecasting errors could be higher) (see e.g., Liu et al. (2020) and the criticism by Petsakos and Rozakis (2022).

It is worth noting that among the 4 sample studies that measure forecasting errors, 2 also address the issue of minimization of forecasting errors through calibration. Mack et al. (2020) measure the forecasting error of a PMP model and an LP model, develop an alternative coupled PMP-LP model, and find that the latter reduces the forecasting error. Maneta et al. (2020) develop a recursive Bayesian estimator that "permits to update the PMP model parameters as new observations become available at time k", while providing a "parameter distribution that reflects the quality of the information used for calibration", thus correcting (albeit *ex-post*) issues related with forecasting errors through recursive calibration.

Finally, it should be noted that all 4 models measuring forecasting errors use fixed origin out-of-sample tests à-là-Heckelei & Britz (2000) and Blanco et al. (2008). This approach can be misleading where the time series contains outliers or abrupt changes that a poor model can predict better (and thus exhibit a superior performance). Alternative techniques such as rolling origin, where holdout and out-of-sample data sizes are modified, can generate a sequence of forecasting error measurements that give a better understanding of how the models perform, thus enhancing the robustness of the validation analysis (Tashman, 2000).

4.2. Incorporation of water inputs

Graveline (2016) dedicates much of its review to the issue of how to better incorporate water inputs into crop production functions, noting that most models still allocate water in fixed proportion to land. Moreover, Graveline (2016) also notes that the CES and (especially) quadratic crop-water functions in use at the time to allow for intensive margin adaptation (i.e., deficit or supplementary irrigation) on top of the extensive (crop portfolio changes among irrigated crops) and super-extensive (crop portfolio changes between rainfed and irrigated crops) adaptation enabled by models that allocate water in fixed proportion to land present significant limitations. Our review shows that 22 of the 119 studies in the post-2016 sample incorporate water inputs through crop-water production functions—a low penetration (18.5 %) that contrasts with the growing evidence on the nontrivial impact that the crop-water production function has on water and economic modeling outputs. For example, Sapino et al. (2022) explore how allowing for deficit and supplementary irrigation can make the water demand function of irrigators "significantly more elastic" as compared to the allocation of water inputs in fixed proportions to land, thus enhancing the cost-effectiveness of instruments like pricing; while Bruno et al. (2024) empirically show how the price elasticity of water can increase dynamically à-là-Samuelson (1947), suggesting changes in the crop-water function that cannot be accommodated by fixed proportion models.

Among the models that integrate crop-water production functions into MPMs (2015–2024), 5 models use discrete functions (piecewise) and 17 continuous functions. Among these publications, 13 are agronomic functions, 6 are CES and only 3 quadratic. The reduction in the use of quadratic functions responds to the limitation highlighted by Graveline (2016), i.e., their inability to approximate the plateau observed in agronomic crop-water production functions. The 6 CES functions in the review are typically calibrated to the agronomic function à-là-Merel et al. (2014) that allow for different substitution elasticities for different inputs; while the remaining 13 studies use agronomic crop-water production functions, albeit the limitations highlighted by Graveline (2016) persist (lack of economies of scale, constant substitution among diverse types of inputs). Some innovations include the distinction between irrigated and non-irrigated crop-water production functions by separating total water availability in an exogenous component made of precipitation and endogenous supplemental irrigation, which enables modelers to differentiate water costs for crop production between wet and dry conditions (Maneta et al., 2020); and the incorporation of multiple inputs in the production function, as it is done by Garnache et al. (2017), who couple the California StateWide Agricultural Production (SWAP) (Howitt et al., 2001) and the biogeochemical model Daycent (Del Grosso et al., 2005) to estimate crop- and region-specific production functions and simulate yield and greenhouse emissions with a and Humblot et al. (2017) who develop a calibration method for two-input (nitrogen and irrigation water) production functions in the AROPAj LP model building on previous work by Godard et al. (2008).

Overall, innovation is limited in this challenge, and crop-water production functions do not show significant variations to those used pre-2016. Although capacity to address (at least some of) water inputs modeling issues already exists, this would add a nontrivial layer of complexity and higher computational costs (Sapino et al., 2022). To adequately resolve this trade-off between model simplicity and realism/cost, we need information on how much accuracy we are gaining—but due to the focus of model validation on calibration errors, it is often unknown how much the incorporation of crop-water production functions improves the forecasting capacity of our model (two PMP, with and without crop-water production function, will yield the same error: zero).

4.3. Incorporation of risk

Graveline (2016) notes that the technical advances towards the incorporation of risk in the objective function through Constant (CARA) or Decreasing Absolute Risk Aversion (DARA) functions (Arata et al., 2014; Petsakos and Rozakis, 2011) had limited penetration in the pre-2016 literature on MPMs for agricultural water reallocation. Importantly, no PMP incorporated CARA, DARA, or any other constant (CRRA) and decreasing relative risk aversion (DRRA) measure pre-2016 explicitly, while LP focused on the minimization of total absolute deviation (MOTAD) of income, which says "nothing about the economic agent's risk preference with regard to either decreasing (constant, increasing) absolute or relative risk aversion" (Paris, 2018). Unnoticed to Graveline (2016), risk was introduced explicitly in the pre-2016 literature on MPMs for agricultural water reallocation through PMAUP (Gutierrez-Martin and Gomez, 2011).

The penetration of risk measures in the literature on MPMs for agricultural water reallocation over 2015–2024 is significantly higher, with 30 publications incorporating risk in the objective function. Risk is modeled in single-attribute implicitly in PMP models (13 publications) and LP Models (2 publications), and explicitly in multi-attribute PMAUP (11 papers) and LP (4 papers). In PMP models, the calibration of the risk parameter is done implicitly through the cost function parameter, where the utility function can adopt different forms, including logarithmic (DARA-DRRA, 4 papers) (Petsakos and Rozakis, 2015) or exponential (CARA-CRRA, 9 papers) (Arata et al., 2014; Liu et al., 2020). A limitation of the more frequently used CARA approach is that it assumes the risk behavior of irrigators does not account for changes in wealth, which is "difficult to accept." In contrast, DARA functions capture this effect, including in data-sparse contexts with insufficient farm-level information (Petsakos and Rozakis, 2015). However, DARA has been criticized for making supply responses "too sensitive" to changes in initial wealth, leading to comparatively higher calibration errors (Liu et al., 2020). Petsakos and Rozakis (2022) argue that model intercomparison and selection should not be based solely on calibration errors but should include assessments based on forecasting errors, which may be more favorable towards DARA. Yet, forecasting errors are absent in all 30 models in the sample that incorporate risk, including those by Liu et al. (2020) and Petsakos and Rozakis (2015).

In the case of PMAUP, risk is modeled explicitly as an independent attribute within a multi-attribute utility function. Typically adopting a Cobb-Douglas functional form, PMAUP balances profit, risk, and other objectives (e.g., labor management) through calibrated weights assigned to each attribute, with risk behavior remaining constant across all wealth levels, implying proportional trade-offs between attributes. The Cobb-Douglas structure inherently supports this behavior because it models preferences as proportions rather than absolute quantities, aligning the PMAUP risk-behavior to CRRA.

4.4. Incorporation of uncertainty

A key objective of MPMs is forecasting, including under environmental (e.g., through yield and water availability changes under climate change) and socioeconomic change (e.g., through price changes), as shown in the co-word analysis in Section 3.2. The conventional approach to forecasting under socioeconomic and environmental change in MPMs is through a mean-variance framework where all plausible futures and their associated probabilities are known, i.e., probabilistic risk. Yet, forecasting MPMs' responses of agents also involves *uncertainties* where modelers do not know, or cannot agree on, (i) the appropriate models to describe the interactions among a system's variables, (ii) the probability distributions to represent uncertainty about key variables and parameters in the models, and/or (iii) how to value the desirability of alternative outcomes (Lempert et al., 2003).

These modeling uncertainties "must be taken in a sense radically distinct from the familiar notion of risk" (Knight, 1921).

Modeling uncertainties are typically classified in three categories (Marchau et al., 2019): 1) input uncertainty emerging from data inputs and assumptions, including forcings (external driving forces influencing the system model and their varying magnitudes, such as water availability or allocation under climate change) and data uncertainty (reliability or accuracy of data inputs describing the baseline situation and quantifying essential aspects of the system under study, such as water use per crop); 2) parametric uncertainty emerging from the calibration process (e.g., CES function, risk parameter); and 3) structural uncertainty emerging from the connections between inputs and variables, among the variables themselves, and their relationship with the final output. 26 of the models in our sample quantify input (6), parameter (13), and/or structural uncertainty (12) (note that some papers quantify more than one type of modeling uncertainty). Structural uncertainty is quantified through the model spread in ensemble experiments that run simulations with alternative model designs (e.g., PMP v LP v PMAUP), while input and/or parameter uncertainties are quantified through sensitivity analyses that run the model with various values for the uncertain inputs (forcings, model data, parameters). Among the sensitivity analyses that quantify input and/or parameter uncertainty, all but one adopt a local sensitivity analysis (scenario-based, One-At-a-Time, and derivative-based local methods) where each input is individually altered to assess impact on outputs while keeping other inputs at their baseline values, then returning the input to its original value before repeating the process for other inputs. The key limitation of this approach is that in nonlinear models where there are interactions between inputs, the impact of each input on the output will change depending on the values of the other inputs, meaning that local sensitivity analysis will only provide a valid measure of uncertainty when the model is linear (the case of LP models, which represent 37,5 % of the sensitivity analyses in the sample) (Saltelli et al., 2019). In the case of nonlinear models such as PMP (representing 62,5 % of the sensitivity analyses in the sample), only global sensitivity analysis that assesses the impact on the output of changing multiple inputs simultaneously (e.g., factorial sampling, Latin hypercube) can provide a valid measure of input and/or parameter uncertainty. However, only one study in our sample conducts a global sensitivity analysis (Rodriguez-Flores et al., 2022), meaning that most of the uncertainty space is unaccounted for (Saltelli et al., 2019). Moreover, no study in the sample implements a "grand ensemble" combining sensitivity analysis and multi-model ensembles to simultaneously quantify uncertainties emerging from inputs, model parameters and model structures.

Two key issues have been used to justify the adoption of partial uncertainty quantifications, including local sensitivity analysis, which can be easily refuted. The first issue relates to the computational cost of more comprehensive uncertainty quantifications, particularly global sensitivity analysis. However, while the adoption of local sensitivity analysis could be justified on the grounds of their lower computational cost a few years ago, workstations (let alone supercomputers) can nowadays perform a comprehensive global sensitivity analysis for most MPM within hours. The second issue relates to the number of factors (inputs, parameters, structures) considered in the analysis: having incorporated all uncertainties, the model output may vary "so wildly as to be of no practical use" (Saltelli et al., 2008). In other words, the conclusions of any sensitivity analysis will be robust enough "if the number and range of input values is wide enough to be credible and narrow enough to be useful" (Leamer, 1985). However, as noted by Saltelli et al. (2008), 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." A similar conclusion is offered by Beven & Binley (1992) and Beven & Freer (2001), who introduced the equifinality concept stating that 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. Typically, a few inputs create most of the uncertainty, and the majority make a marginal contribution. This is visible in most global sensitivity analysis, where first (changing one input) and second order (changing two inputs simultaneously) effects explain most of the variation in the output, with third and higher order effects having a marginal impact (Puy et al., 2022c). We thus argue that, despite improvement with respect to the pre-2016 situation where uncertainty quantification was limited to a few scenario-based local sensitivity analysis, this improvement has not kept pace with that of other scientific domains and disciplines, including within economics (e.g., econometrics). Enhancing the penetration of uncertainty analysis in the MPMs community should be considered a top priority—especially considering that most models are not sufficiently validated either.

4.5. Spatial detail

The spatial scales at which the MPMs are calibrated can significantly influence the behavior of agents in the model, water use decisions, and policy implications (Graveline, 2016). Water users are subject to heterogeneous conditions, with fundamental differences in technology endowment, preferences, and constraints (including water availability). The choice of spatial detail is linked to the problem definition that the modeler wants to explore and typically includes three scales, whose relative relevance has remained largely unchanged with respect to Graveline (2016): farm level (24,57 % of studies in our sample), regional scale (71,18 %), and hybrid approaches (4,23 %).

Farm-scale modeling allows us to explore farmers' individual behavior and choices considering the actual technology endowment, preferences, and constraints, and has been adopted for policy analysis, notably CAP reforms (Ciaian et al., 2020), as well as in studies incorporating risk (Arribas et al., 2020). However, modeling at the farm level involves a non-trivial use of resources as compared to the alternatives. Data at a farm scale can be difficult to find, and where available is typically anonymized, which precludes the geographical location of each individual farmer that is necessary to conduct spatially distributed studies at a basin scale (European Commission, 2019). Thus, water economists modeling at farm scales may need to resort to ad-hoc surveys to obtain spatially distributed data, significantly increasing the cost of the study as compared to the alternative of regional-scale modeling—-which is typically preferred. A breakthrough in this regard as compared to the situation in 2016 has come from recent advances in satellite-based irrigation data, which is producing increasingly accurate and disaggregated information on key physical variables such as land, yields and water use, thus allowing for the substitution of expensive and potentially biased (due to strategic responses, especially in the case of studies on noncompliance such as water theft) survey data with open-data from satellites. This spatially distributed and open data is not available for economic variables such as costs or prices, though. Accordingly, the few economic calibrated MPMs using satellite-based irrigation data (Maneta et al., 2020; Sánchez-Daniel et al., 2024) model at a regional-scale where the complementary economic data is readily available.

Regional-scale is the most commonly adopted modelling level in our sample and can be implemented through a wide array of aggregation units ranging from irrigation districts (31 papers), countries (12), secondary administrative divisions (a highly heterogeneous group comprising EU's NUTS2,[1] Chinese provinces, and US states, *inter alia*) (15), tertiary administrative divisions (including EU's NUTS3 or municipalities, US counties or boroughs, and Chinese prefectures, *inter alia*)

[1] The **Nomenclature of territorial units for statistics**, abbreviated **NUTS** (from the French version ***N****omenclature des* ***U****nités* ***t****erritoriales* ***s****tatistiques*), is a geographical nomenclature subdividing the territory of the European Union (EU) into regions at three different levels: NUTS 1, 2 and 3, moving from larger to smaller territorial units.

(8) or river-basins (4), to the less frequently used biomes (2), altimetric zones (1) or clustering (by technology endowment, income, or farm typology) (3). Key persisting challenges of regional scale modeling include hydrological integrity where the aggregation unit spans over disconnected water bodies, which may lead to unrealistic water reallocation outcomes (particularly relevant at coarse spatial aggregation levels such as countries or secondary administrative divisions); and aggregation bias that overlooks preferences, technology or resource disparities among irrigators (Chakir and Parent, 2009). Over the past decade these limitations have been addressed, as was done previously (Graveline, 2016), by increasing the granularity of aggregation units (including through novel clustering methods, see e.g., Cortignani & Dono (2015)).

Hybrid approaches combine both regional- and farm-scales to account for heterogeneity in the aggregation. An example of hybridization is the CAPRI model, which combines farm and regional data to avoid aggregation bias in the calibration of the model (Ewert et al., 2011). A key limitation of the hybrid approach adopted by CAPRI is that model agents are aggregated at the level of NUTS2 (e.g., this yields 17 agents in Spain), spanning over multiple disconnected water bodies inside which water can be freely reallocated, thus violating hydrological integrity (Britz and Witzke, 2012). Leveraging increase in computational power, more recent hybrid approaches achieve higher granularity using the same farm-level data as CAPRI (Farm Accounting Data Network), thus addressing aggregation bias while observing hydrological integrity. Examples include Cortignani and Dono (2015), who calibrate at an irrigation district scale using hierarchical and non-hierarchical clustering methods that select the preferable number of farm-cluster groups and maximize the internal similarity of groups by k-means; and Cortignani and Dono (2019), who group farm samples by geographical and altimetric level to account for farm specialization. However, hybrid approaches are adopted by a minor fraction of the models in the sample.

4.6. Data validation

There is a growing research body that highlights the vulnerabilities of MPM calibration and forecasts to measurement errors or biased reporting in data (Foster et al., 2024), which compounds insufficient input uncertainty quantification (Puy et al., 2022a). This is particularly relevant for the case of water use data, which is prone to errors (e.g., in monitoring or estimates) and biases (e.g., strategic responses of farmers reporting water use) in measurement (Loch et al., 2020). Over the past decade, data validation has been highlighted as a key step to achieve reliability and robustness in water modeling and management (Puy et al., 2022b), and research on water use monitoring has experienced a significant growth through in situ (e.g., sensors, water metering) and remote sensing-based (Higginbottom et al., 2021) monitoring—albeit errors and uncertainties remain high (Foster et al., 2024). Yet, only 2 MPMs in our 2015–2024 sample explicitly address data validation issues in model design (Maneta et al., 2020; Sánchez-Daniel et al., 2024). Both papers explore the influence of alternative water use data sources on model calibration and simulation outputs, suggesting that in these particular cases remote sensing technology can produce more reliable water use data than conventional survey data (which is typically collected through anonymized farm surveys with limited granularity and subject to strategic responses in self-reporting) (Maneta et al., 2020) or estimates from hydrologic or agronomic models (which are subject to nontrivial forecasting errors) (Sánchez-Daniel et al., 2024). Noteworthy, remote sensing data is not a panacea, and translating agricultural water consumption (from NDVI indices) into estimates of water withdrawals or applications at field scales needed to support MPMs, is also subject to nontrivial uncertainties and errors, which may exceed in some other cases those of conventional survey or modeling methods. Two other models in our sample explore water use data input uncertainty through sensitivity analysis using fuzzy sets (Zhang et al., 2021, 2022) and interval approach (Wang et al., 2022), but do not validate the data.

Adoption of new technologies and practices has become increasingly addressed in recent MPM research, overcoming earlier limitations identified by Graveline (2016), which were mainly due to the lack of relevant technical and economic information. Our review finds that, since 2015, a growing number of studies incorporate technological change, especially deficit/supplementary irrigation, but also innovations such as organic farming (Galnaityte and Krisciukaitiene, 2016; Prisenk and Turk, 2015), desalination (Baum et al., 2016; Welle et al., 2017), health-related interventions (Kassie et al., 2020), climate-smart agriculture (Dunnett et al., 2018), and eco-schemes (Baldi et al., 2023). However, most of these are simulated using LP-based models, as non-linear MPMs face greater challenges integrating new practices due to the difficulty in calibrating the nonlinear components of the objective function (Graveline and Mérel, 2014). Notably, model coupling—such as integrating MPMs with CGE or ABM frameworks (Baum et al., 2016; Baldi et al., 2023)—has emerged as an effective strategy to overcome these limitations, allowing more realistic representation of market, learning, and replication dynamics. Ultimately, the capacity of MPMs to capture technology adoption is less a function of calibration method than of the availability and quality of underlying data, echoing the central role of data validation highlighted earlier.

Far-from-reference simulations, which test MPMs under conditions well outside their calibration range, expose the limitations of traditional models reliant on historical data (Graveline, 2016b). Our sample includes studies stress-testing MPMs under scenarios such as nuclear winter (Wilson et al., 2023), extreme climate change (Gohar and Cashman, 2016; Dunnett et al., 2018; Wineman and Crawford, 2017; Zelingher et al., 2019; de Moraes et al., 2018), and abrupt policy shifts (Layani et al., 2023). These works increasingly couple MPMs with external models to simulate nonlinear, abrupt, or disproportionate changes in key exogenous variables, aiming to assess the robustness and adaptability of model outputs. However, evidence shows that as real-world conditions deviate further from historical norms, adaptive responses may become abrupt and unpredictable (UNDRR, 2021; Loch et al., 2020; Wilson et al., 2023), and MPM parameters themselves may lose structural validity (Saltelli et al., 2019). This underscores the need for novel, micro-founded, and behaviorally informed models (Koundouri et al., 2023; Pradhan, 2021; Safarzyńska, 2018; Wuepper et al., 2023), but also highlights that the main bottleneck is often the availability of reliable, forward-looking data. As such, both the ability to simulate technological adoption and the validity of far-from-reference predictions ultimately depend on advances in data collection, integration, and validation—reinforcing the centrality of rigorous data validation practices in advancing the field of MPMs.

4.7. Coupling

Several of the MPMs challenges discussed above stem from exogenous variables to the model. One way to address these challenges involves coupling the MPM to an external sub-model that explores the challenge more in depth using relevant techniques to that specific subfield. For example, to quantify input uncertainty in prices, a modeler can resort to an external CGE sub-model that simulates pricing scenarios, obtain probability distributions for these variables, and run Montecarlo simulations with them using the MPM. Similar approaches using external sub-models can be employed to address incorporation of water inputs (e.g., through external agronomic models), adoption of new technologies and processes (e.g., through ABM), or far from reference simulations (e.g., GCM).

In this context, model coupling has received growing attention during the past decade, with 28 studies in our sample incorporating some type of model coupling. Note that to qualify as a coupled model in our review, the resultant integrated model must include a full-fledged MPM. Holistic approaches that use part of or a simplified version of a MPM, such as an MPM-based piecewise demand function that is integrated into the architecture of a hydrologic model, do not appear in the review. Accordingly, the coupled papers in our sample adopt a modular approach, meaning that models at each system level are run independently in modules, and then integrated through sets of protocols, which are rules designed to manage the interconnections among models (Csete and Doyle, 2002). The protocols adopted in 9 of the studies are bidirectional/two-way, where the MPM and coupled model feedback to each other, an approach that has been commonly used in the discipline of sociohydrology (Pande and Sivapalan, 2017; Sivapalan et al., 2012); while in 19 studies the protocol is one-way, where the coupled model produces inputs (e.g., agronomic production function, climate change scenarios, commodity prices) to feed the MPM simulations. Most of the models coupled to MPMs represent socioeconomic systems, notably through CGE (5 studies), ABM (1), MRIA (1), Analytic Hierarchy Process (1). Other system models coupled to MPMs include hydrologic, through Aquatool (1), HEC-HMS (1), WEAP (2), MODSIM (2), System Dynamic Model (1) Qual2K (1), Model Predictive Control (3), Artificial Neural Networks (2), HBV (1); climatic, through GCM (4) and LARS-WG (1); and environmental through LCA (2), MAGPIE (1), LPJmL (1). Finally, while most couplings are developed adopting a static setup (25 studies) and offer a 'snapshot' of the integrated system (Aghapour Sabbaghi et al., 2020; Hassani and Hashemy Shahdany, 2019; Parrado et al., 2019), 3 studies allow the incorporation of dynamics by means of connecting time-variant hydrologic models (HBV, HEC-HMS, Aquatool) to the otherwise static MPM (Maneta et al., 2020; Pérez-Blanco et al., 2021a; Pérez-Blanco et al., 2021b), thus representing the co-evolution of the human and water system across multiple timesteps.

A major limitation to coupling efforts in MPMs is that they have not been organized around a common framework that allows a more systematic design and validation, as has been occurring in other scientific areas such as ecological modeling of climate change (Eyring et al., 2016; Warszawski et al., 2014) or water systems (Schaake et al., 2006). A community-agreed framework is necessary towards mainstreaming microeconomic MPMs research into major climate change forecasting scientific endeavors, as has been done in the field of macroeconomics through Integrated Assessment Models (IAM). As an example of the benefits this integration may yield, attribution science, a field of study within climate change research that aims at measuring how ongoing climate change directly affects extreme events and their damages in areas like droughts and agriculture, does not account for the adaptive behavior and responses of agents and how they affect the impacts of weather extremes. Agents' responses are thus assumed to be proportional, i.e., a 50 % reduction in water availability will lead to a 50 % reduction in water application to each crop without changes in the crop portfolio. Addressing this and other limitations necessitates the development of a common framework and guidance for the design of coupling experiments that integrate MPMs into the climate and other ecological modeling communities—an effort from which both the scientific community and society will benefit.

5. Conclusions and recommendations

This study reviews and critically discusses the evolution of *calibrated* MPMs for agricultural water reallocation over the past decade, following up on the last available review by Graveline (2016). Our bibliometric review shows an increase in the number of publications on the topic, where the average number of papers published per year during 2015–2024 almost tripled compared to those published in the previous 25 years (1990–2014). Integration across MPMs sub-fields is limited, with a wedge between papers focused on addressing calibration and technical aspects in PMP and multi-attribute and coupled papers. The systematic review shows some advances across the 9 key research challenges, but also significant gaps. Building upon our review and discussion, we propose the following recommendations for future research:

1) Forecasting errors should be measured, ideally through rolling origin or similar methods that offer more robust performance indicators, to *validate* MPMs. Model validation is instrumental to inform model intercomparison and selection, particularly in the design of crop-water production functions (*water inputs*) and the *incorporation of risk* in MPMs.
2) *Validate data*, particularly water use data, leveraging recent advances in monitoring. Where data validation is not feasible or inconclusive (e.g., due to data constraints), input uncertainty should be quantified.
3) Separate the topics of *uncertainty* and *risk*. Risk is but one type of uncertainty, and the semantic confusion between the two leads to broad-brush uniform approaches that are inadequate to deal with higher levels of uncertainty.
4) Define a protocol for *uncertainty* quantification in MPMs that includes, at the very least, a global sensitivity analysis of input and parameter uncertainties. Where the paper is applied/empirical (i.e., the contribution is not a new calibration method or similar technical development), the modelers should compare, as much as possible, the outputs from multiple models in ensemble experiments to quantify structural uncertainty.
5) Exploit model coupling to enhance *spatial detail* (e.g., hydrologic models working at a basin scale, ABM working at the meso-scale, CGE models working at the macroeconomic scale) and explore the *adoption of new technologies and processes* (e.g., through ecological models that simulate relevant technological processes, such as yield of novel crops) and *far from reference simulations* (e.g., through GCM).
6) Develop novel structural models that more strongly rely on microfoundations, especially through the integration of cognitive processes identified in the behavioral economics literature (e.g., learning and replication, regret, loss aversion), to enhance our forecasting ability, including in *far from reference simulations.*
7) Develop a common framework and guidance for the systematic design of coupling experiments that underpins the integration of MPMs into major climate change forecasting scientific endeavors such as AgMIP, ISIMIP, or CMIP. This will bring benefits for scientific research through more detailed and accurate representation of agents' adaptive behavior, while bringing higher visibility to microeconomic MPMs research (as has happened with macroeconomic research).

These major recommendations, and the complementary scientific debate to further refine them, have the potential to overcome the novel and persisting research gaps in MPMs for agricultural water reallocation. We invite MPM researchers to join this debate, critically assess the state of the art and research gaps, and contribute to develop relevant advances that enhance the ability of MPMs to inform robust agricultural water reallocations.

CRediT authorship contribution statement

Giammauro Soriano: Investigation, Data curation, Writing – original draft, Visualization, Methodology, Formal analysis. **Francesco Sapino:** Writing – review & editing, Formal analysis. **C. Dionisio Pérez-Blanco:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2025.106628.

Data availability

Data will be made available on request.

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