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Review article

# Managed Aquifer Recharge: Modeling approaches to integrated assessment of groundwater interventions

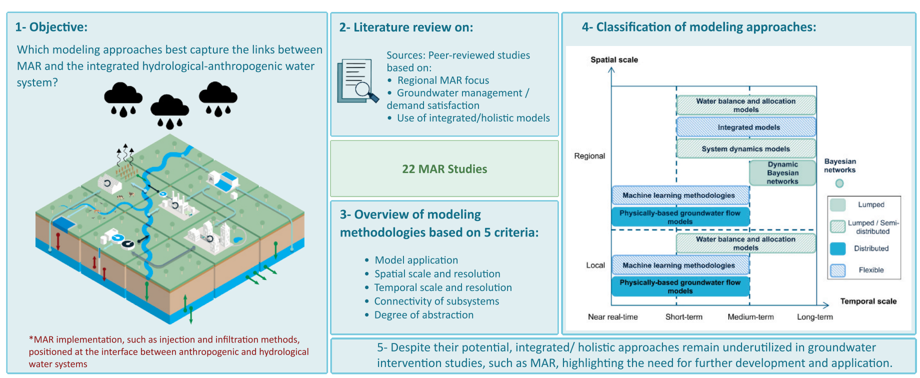
Mina Yazdani [a,b,*], Peter van Thienen [a], Sija F. Stofberg [a], Marjolein H.J. van Huijgevoort [a,c], Ruud P. Bartholomeus [a,b]

[a] KWR Water Research Institute, Nieuwegein, the Netherlands
[b] Soil Physics and Land Management, Wageningen University & Research, Wageningen, the Netherlands
[c] Institute for Environmental Studies, Vrije Universiteit Amsterdam, Amsterdam, the Netherlands

## HIGHLIGHTS

- Classic MAR modeling often ignores regional water system-level interdependencies.
- Examples show integrated/holistic models' potential to assess MAR regional impacts.
- Focusing on parsimony drives adoption of integrated models for sustainable MAR planning.

## GRAPHICAL ABSTRACT

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## ABSTRACT

Groundwater resources are under increasing pressure due to water abstractions and climate change, leading to water scarcity problems and threats to groundwater-dependent ecosystems. Managed Aquifer Recharge (MAR) techniques offer a promising strategy for mitigating water scarcity problems and advancing sustainable management of groundwater resources. These measures aim at intentional recharge and storage of water in aquifers by linking periods of surplus with periods of shortage to overcome the temporal imbalance. While MAR has traditionally been implemented at local scales, growing challenges related to water scarcity and groundwater depletion have led to their increasing adoption across broader regions. This shift highlights the need for modeling approaches that can adequately represent MAR within regional water systems, emphasizing interactions with both hydrological and anthropogenic components while allowing investigation of trade-offs when planning these measures. This paper provides an overview of the modeling methodologies used to assess MAR interventions in a regional context. We begin by discussing the inherent complexity of the effects of groundwater interventions such as MAR at the regional level, particularly regarding water quantity. We then look into a range of modeling approaches available in the literature to capture these complexities, based on the modeling objective, data

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* Corresponding author. Soil Physics and Land Management, Wageningen University & Research, Wageningen, the Netherlands.
*E-mail address:* mina.yazdani@wur.nl (M. Yazdani).

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availability, and the required spatial and temporal scales. We further emphasize the importance of incorporating multiple levels of uncertainty throughout the planning and implementation of MAR projects and model-based analyses. Our study highlights that, despite their promise, integrated and holistic modeling approaches remain underutilized in groundwater research, including MAR, highlighting a need for broader development and adoption.

## 1. Introduction

### 1.1. Context

The changing climate over recent decades (Copernicus Climate Change Service & World Meteorological Organization, 2025) has caused significant stress on water resources across Europe (Bartholomeus et al., 2023; Douville et al., 2021; Tabari et al., 2015), adversely affecting both surface and groundwater systems, and based on climate projections, more is yet to be expected. Groundwater resources, in particular, are under increasing pressure due to intensified abstractions and the impacts of climate change, contributing to water scarcity problems and threatening groundwater-dependent ecosystems. Moreover, secondary impacts such as salinization and disruptions to water availability across sectors including industry, energy, agriculture and drinking water supply pose additional challenges (Deltaprogramme, 2023; Psomas et al., 2021)

To address the challenges associated with groundwater resources, a range of strategies are being implemented. These include both demand side interventions such as water pricing (Portoghese et al., 2021) and water conservation campaigns, as well as supply side interventions such as restrictions on groundwater extraction (Theesfeld, 2010), land management strategies, Nature-Based Solutions (NBS), and Managed Aquifer Recharge (MAR) (Zhang et al., 2020). While many of these measures have been implemented at local scales (Zheng et al., 2021), growing challenges related to water scarcity and groundwater depletion are driving their adoption across broader regions. This trend reflects transition in water landscapes (Bartholomeus et al., 2023), as regions adapt to shifting hydrological conditions and recognize the need to upscale these implementations to large-scale solutions. This highlights the necessity for coordinated management of groundwater and related resources, by clearly describing competing objectives and trade-offs, and balancing the needs and values of diverse stakeholders (Jakeman et al., 2016). Especially at regional scales, this aspect becomes critical since different water users, such as urban, agricultural, industrial, and environmental sectors, face unique challenges and have dynamic needs such as varying requirements for timing, quantity, and quality of water, as well as vulnerability to shortages. At the same time, sources of supply such as groundwater and surface water each behave differently over various time scales (e.g., response times to changes such as rainfall or withdrawals), reflecting their distinct dynamics. This variability further complicates water management, as both sources are subject to complex and changing climatic and anthropogenic conditions.

In this context, by thinking in terms of interdependencies between water streams across sectors (Fig. 1), i.e., between the anthropogenic system (e.g. drinking water production, industry, urban areas, agriculture (irrigation) and wastewater treatment (Pronk et al., 2021)) and hydrological systems, we move beyond traditional “silo-thinking” (Bach et al., 2014). This integration helps identify what is and is not feasible when implementing measures across hydrological and urban water systems. However, despite being less frequently documented, the literature does contain examples of where such implementations have

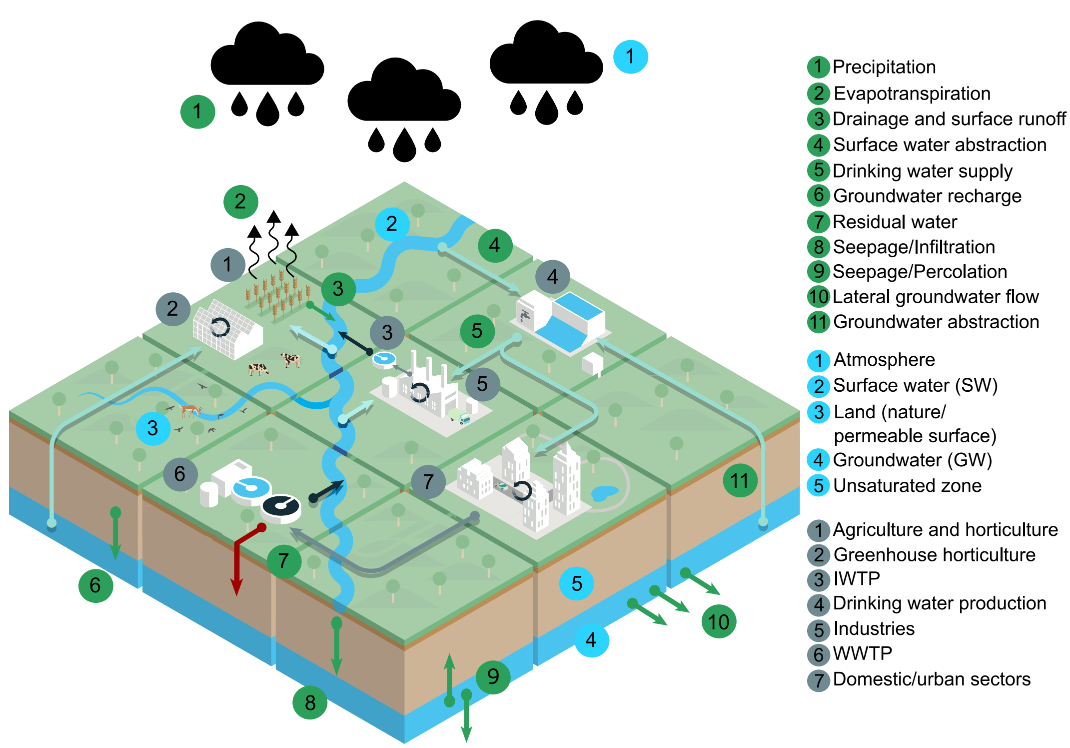


**Fig. 1.** Integrated hydrological and anthropogenic water system. This figure illustrates the integrated water system including hydrological (in blue) and anthropogenic (in grey) components along with the processes (in green) that link them together, creating interconnections and dependencies. Various feedback loops are present between the hydrological and anthropogenic water system. The red arrow indicates MAR using treated wastewater, affecting flow to surface water and dependent services. IWTP: Industrial Water Treatment Plant, WWTP: Waste Water Treatment Plant. Adapted from (Stofberg et al., 2025)

caused unintended consequences, i.e., "negative externalities" (Alam et al., 2022; Glendenninga and Vervoort, 2011). Thus, it is important to understand the interactions between infrastructural and policy measures, in addition to how they influence hydrological and anthropogenic water systems, which can foster more sustainable planning and development (Di Baldassarre et al., 2018).

### 1.2. Managed Aquifer Recharge

Among the range of groundwater management strategies, Managed Aquifer Recharge (MAR) is widely recognized as an effective technique for addressing water scarcity and pressure on groundwater systems. MAR involves the deliberate recharge and storage of water in aquifers during periods of surplus, with the intention of recovering it during drier periods (Bouwer, 2002; Sprenger et al., 2017), delivering environmental benefits and supporting conjunctive use of multiple water sources (Van der Gun, 2020). As a result, it helps balance water availability across time and overcome temporal mismatches between supply and demand (Zhang et al., 2020).

To facilitate aquifer recharge, different sources of water such as storm water, surface water from rivers or lakes, treated wastewater, or groundwater from other aquifers can be utilized (Sprenger et al., 2017; Zhang et al., 2020). Combining these sources with MAR not only enhances groundwater availability, but also creates interdependencies across the water system, where groundwater level dynamics become influenced by the variability of external sources such as surface water flows, stormwater, or reclaimed water inputs. This change also in turn can influence the timing, availability and management of the external sources. Therefore, whether a MAR scheme is urban-sourced (source water from anthropogenic water flows), urban-serving (benefiting urban populations), or non-urban (serving agricultural, environmental, or rural purposes with non-urban sources) determines the necessity of explicitly integrating anthropogenic water system dynamics into the decision-making process. For example, treated wastewater (urban-sourced MAR) offers the advantage of year-round availability; however, conservation measures during droughts (due to its connection with surface water flows) may reduce the volume of treated effluent available for recharge (Dillon et al., 2022).

MAR applications can be assessed using different approaches depending on the objectives and scale of analysis. At site-specific level, different techniques such as geochemical and isotope tracer methods are widely employed during feasibility, design, and monitoring stages, and for evaluating MAR impacts. These methods provide critical insight into subsurface processes including spreading and mixing processes of the source water and the ambient groundwater (Ganot et al., 2018), residence times and flow pathways, or sensitivity of subsurface flows to pumping regime and infiltrations rates (Moeck et al., 2017). They also provide information into water quality evolution in the ambient groundwater as a result of MAR implementation (IAEA, 2013), capturing fine-scale hydrogeological interactions. While these measures are invaluable in site-specific investigations, they can be limited in their ability to extrapolate beyond the measurement extent. In this context, tracer data can be used to inform models in order to extend such insights to broader spatial and temporal scales (Ganot et al., 2018), and testing alternative scenarios.

Therefore, modeling methodologies have proven useful in supporting decision-making, as well as in understanding and evaluating these interventions. Ringleb et al. (2016) investigated field, laboratory and theoretical MAR case studies which applied commonly used software codes and tools, including groundwater flow, unsaturated flow, solute transport, reactive transport and watershed or water balance models to evaluate MAR applications. They classified the use of such process-based models with respect to MAR type. They concluded that groundwater flow models combined with solute or reactive transport algorithms are the most widely used for MAR assessments, especially for local (site)-scale feasibility, design and impact assessments.

In another study, Sallwey et al. (2018) conducted a comprehensive evaluation of unsaturated zone (vadose zone) models for assessing MAR through a review of 16 studies. The analysis underscored the critical role of these models in planning and optimizing MAR systems, as well as in quantifying MAR impacts on both the vadose zone and underlying groundwater. Similarly, Kloppmann et al. (2012) assessed the use of groundwater models for site selection, feasibility analysis, pre-dimensioning of the MAR system (Zuurbier et al., 2015) and design of the associated monitoring system, with a focus on water quality aspects. Modeling studies have shown potential in assessing clogging occurrence (Lippera et al., 2023) and precise scheduling of recharge and recovery rates (Kacimov et al., 2016; Zuurbier et al., 2014). Despite the availability of various modeling approaches for assessing the feasibility and effectiveness of MAR applications, an overview of the model-based studies that explicitly represent MAR's role within the broader water system (Fig. 1) remain limited. While previous reviews, such as Ringleb et al. (2016) and Sallwey et al. (2018), have focused on site-scale MAR modeling and feasibility assessments, and Kelly et al. (2013) outlined general modeling approaches for integrated environmental modelling, this manuscript extends those foundations, by bringing the focus to regional-scale MAR and its integration within complex water systems.

In their review, Ringleb et al. (2016) observed that watershed or water balance models, which partly consider an integrated water resource management approach, were applied in only a few cases, including in-channel modifications, rainwater harvesting and one case of well and borehole schemes. The authors emphasized the need for holistic models that allow integration of groundwater, surface water and unsaturated zone in MAR studies, leading to a more complete representation of the hydrological system - although they did not consider the inclusion of anthropogenic subsystems into model-based analysis of MAR cases.

More recently, the concept of Co-Managed Aquifer Recharge (European Commission, 2025) has been introduced to link MAR with multi-level governance through a participatory approach, aiming to enhance collective awareness of groundwater exploitation. Therefore, modeling approaches that facilitate this level of understanding should become tools not only for planners but also for MAR practitioners, enabling them to take initiative in understanding and managing MAR dynamics within the water system, considering both local conditions and consumptive flows, so that the sustainability of these interventions at the regional level can be ensured. These approaches offer valuable means to translate integrated thinking into quantitative tools that support scenario analysis, stakeholder engagement, and informed decision-making.

Therefore, to understand the effectiveness of MAR strategies at the regional scale, and to investigate their cumulative effects (Ros and Zuurbier, 2017), models need to represent interactions within the integrated hydrological and anthropogenic water system, extending beyond groundwater alone. As shown in Fig. 1, MAR applications especially when combined with water reuse, lie at the interface between anthropogenic and natural water systems, by redirecting water from one source to the other, altering water flows and impacts across the hydrological and urban water systems. Accordingly, focusing on feedbacks and interconnections within the whole system is necessary to identify how the effects propagate, and investigate possible adverse consequences and trade-offs.

For instance, during MAR, injecting surface water, stormwater, or treated wastewater can reduce discharge to surface water, reflecting the trade-off between slow (subsurface) and fast (surface) hydrological processes, potentially delaying and shifting hydrological regimes (Ghasemizade et al., 2019). In addition, over long periods, increased water availability enables higher water demand, which can unintentionally lead to higher and unsustainable water resource exploitation (Di Baldassarre et al., 2018). Moreover, in some hydrogeological settings, the surface-groundwater interaction in MAR applications allows a dynamic storage and redistribution between these resources. Therefore, considering these interconnections leads to responsible implementation of groundwater management strategies such as MAR, through an integrated and systemic approach (Bartholomeus et al., 2023; Dingemans et al., 2020; Pronk et al., 2021)

### 1.3. Aim

The objective of this article is to provide insight into the methodologies and modeling frameworks available for assessing the effectiveness and the impacts of MAR on the regional water system (Fig. 1), focusing on water quantity aspects. To achieve this goal, the paper goes beyond existing literature by: (i) classifying modeling approaches based on their ability to represent feedbacks, subsystem connectivity, and spatial-temporal contexts, (ii) synthesizing examples from MAR and other groundwater interventions to illustrate transferable modeling strategies, (iii) highlighting gaps in current MAR literature, especially regarding the lack of integrated assessments that include the combined effects within the water system. These classifications help further determine the relevant temporal and spatial scales, and show how multiple approaches can be adapted or combined to support integrated assessment (Fig. 2) for MAR.

Moreover, we aim to contribute to the existing understanding of MAR phases and objectives at local and regional scales by identifying which models are best suited for specific contexts. To this aim, we build on insights from previous review studies in this domain.

## 2. Methods

We present the methodology employed towards assessing different modeling approaches available for studying MAR applications at the regional scale. This includes a set of criteria, defined to guide the assessment and comparison of the available approaches, with a focus on their capacity to simulate interacting processes and feedbacks within the integrated hydrological and anthropogenic water systems, as also indicated in Fig. 1.

Furthermore, we draw on case studies from peer-reviewed journals and conference proceedings, and employ a snowballing strategy by examining the reference lists of previously identified publications. These studies were retrieved via Google Scholar and Scopus using a combination of search keywords, including “MAR”, “artificial recharge”, “modeling”, and “integrated model”. The inclusion criteria for the subsequent choice of articles were: (i) a focus on model-based analyses, particularly those addressing the regional dimensions of MAR applications, (ii) aimed at groundwater management and/or in relation to demand satisfaction, (iii) focusing on the use of integrated or holistic models (Fig. 2), (iv) studies published in English. Therefore, pilot-scale MAR studies without regional/system-level implications were excluded from the reviewed articles. Studies focusing exclusively on water quality or geochemical processes without water quantity modeling, non-peer-reviewed sources (e.g., reports, grey literature) and studies without a modeling component were also excluded. For each selected study, we extracted key attributes: modeling methodology, subsystems represented, MAR phase addressed, source water type, and the five criteria from Section 2.1 (objective, spatial and temporal scale and resolution, connectivity of subsystems, and degree of abstraction). These elements informed the comparative analysis in Table 1. The examples were chosen for their thematic relevance and their potential to reflect real-world implementation of MAR within the complex regional water system. Overall, 22 studies were collected, and were assessed against the criteria mentioned below.

### 2.1. Criteria

Here, we present the criteria used for assessing the applicability of various modeling approaches for holistic assessment of MAR within a regional context, focusing on the integrated water system shown in Fig. 1. The following criteria, explained below, guide the selection of the modeling approaches:

- Model application
- Spatial scale and resolution
- Temporal scale and resolution
- Connectivity of subsystems
- Degree of abstraction

These criteria are not meant to be considered in isolation; rather, they reflect model features that are related and often require trade-offs. For example, the purpose of model application might call for a high level of spatial detail, but this could be constrained by computational limitations or data availability associated with a certain degree of abstraction. The modeler might therefore make a choice based on the most limiting factor.

#### 2.1.1. Model application

The purpose for which a model is employed is the primary driver in selecting the appropriate modeling approach, as it defines the questions to be answered. Clearly defining the model’s intended application guides the inclusion of processes and parameters, as well as the choice of spatial and temporal resolution and the required level of abstraction. In MAR contexts, whether models are applied to facilitate planning, design, or operational decisions also influences these choices to ensure they align with the objectives of the analysis.

#### 2.1.2. Spatial scale and resolution

Hydrogeological and anthropogenic processes in water systems function across multiple spatial scales, necessitating models that can accurately capture scale-dependent dynamics. The spatial resolution of these models critically affects their accuracy and relevance, depending on study objectives. Various spatial representations have been used in modeling the underlying hydrogeological and anthropogenic processes. Commonly, they are classified as *distributed* (i.e., the model considers spatial variations in process representation), *lumped* (i.e., the spatial domain is treated in an aggregated or averaged manner), and *semi-distributed* (i.e., the modeling domain is divided into sub-sections that are internally homogeneous, but externally distinct).

#### 2.1.3. Temporal scale and resolution

Temporal scale and resolution are critical considerations in modeling of the integrated water system, as different subsystems (e.g., groundwater vs. river flow) respond over varying timeframes. In addition, the dynamics of anthropogenic components are dependent upon climatic conditions, industrial and agricultural productions, human consumption patterns, and supply availability, among other factors. This variability complicates selection of the modeling methodology that integrates proper temporal dynamics, particularly when assessing the impacts of interventions. The choice of temporal scale (i.e., horizon) and resolution should align with the study’s objectives to ensure key processes are captured. Models typically treat time in three ways: steady-state (assuming equilibrium conditions and neglect temporal changes); lumped, discrete temporal models (which produce output for a single time period, e.g., an average groundwater storage value over 30 years); and dynamic quasi-continuous models (which generate output at each time step, producing a time series of the output variable) (Kelly et al., 2013). With regard to the temporal scale of analysis, the models may be applied across four time horizons: near real-time (minutes to several days), short-term (weeks to months), medium-term (1–30 years), and long-term (30–100 years).

#### 2.1.4. Connectivity of subsystems

Models of the integrated natural and anthropogenic water systems (Fig. 1) represent the interactions between system components either as one way (cause-effect) or feedback (two-way) connections. The ability

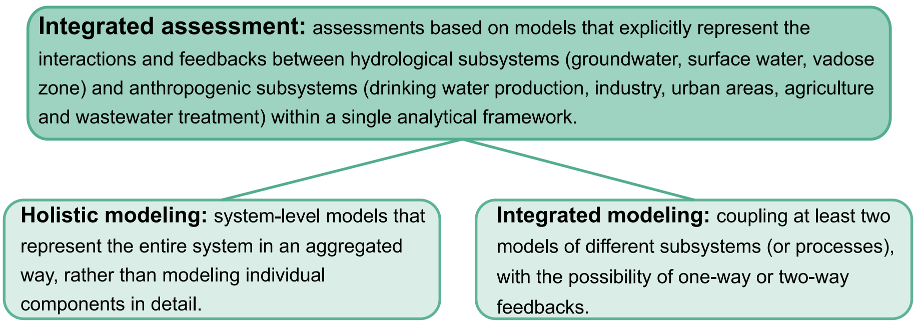


**Fig. 2.** Definitions of Integrated assessment, holistic and integrated modeling.

to incorporate feedbacks, which is crucial in complex systems (Sec. 2.1), is a key modeling criterion. In Water Evaluation and Adaptation Planning (WEAP) (Stockholm Environment Institute, 2025), for example, water availability constrains supply, which limits delivery volumes to users. However, demand is typically predefined and does not adjust dynamically within a single model run based on delivered volumes, indicating a lack of internal feedback between water availability and demand regulation. Such feedbacks need to be explicitly included through customized modifications. In addition, incorporation of feedback processes allows to incorporate nonlinearities in boundary conditions of the system, as opposed to static ones.

#### 2.1.5. *Degree of abstraction*

Due to the complexity of the integrated hydrological and anthropogenic water system, the degree to which a model simplifies the real world can vary significantly (Moradkhani and Sorooshian, 2008). This depends on factors like the modeler's experience (Beven, 2012), data availability, and the required level of detail (spatial, temporal). These aspects are captured by the term *degree of abstraction*,[1] which reflects how much real-world processes are aggregated in the model. This often involves using generalized relationships in order to represent multiple functional elements as single, composite units. Therefore, a low degree of abstraction offers a detailed representation (Borshchev and Filippov, 2004), whereas a high degree of abstraction corresponds to a more simplified and generalized representation (less detail). Additionally, more detailed (less abstract) models typically require more data and computational resources.

## 3. Overview of modeling approaches

This section presents an overview and classification of the modeling approaches used in the reviewed literature to study MAR within regional water systems.

In order to connect modeling choices with MAR planning and practice, we describe the underlying mechanisms in each modeling method, and how it aligns with decisions across MAR phases and scales (site to region). Although many methods originate from general hydrogeology or systems modeling, their adoption for MAR is relevant by considering; e.g., process-based models for site-scale feasibility and design analyses (Ringleb et al., 2016; Sallwey et al., 2018), water balance/allocation tools for catchment-scale portfolio and reliability planning (Clark et al., 2015; Gómez et al., 2006), and holistic/integrated models for regional assessments and planning, involving anthropogenic-hydrologic systems (Ghasemizade et al., 2019; Hanson et al., 2014).

### 3.1. *Numerical process-based groundwater models*

Numerical process-based groundwater models, including groundwater flow, unsaturated (vadose zone) flow, solute transport, and reactive transport models have been widely used in MAR projects (Ringleb et al., 2016). These models allow flexible spatio-temporal representation of hydrological system processes, provided that proper data on system properties is available for model calibration. In local scale assessments, model design/or choice must reflect the processes and subsystems relevant to the specific MAR technique (surface spreading, in-channel modifications, well/shaft/borehole recharge, bank filtration, rainwater harvesting (Sprenger et al., 2017)). For instance, Sallwey et al. (2018) emphasized the critical role of unsaturated zone (vadose zone) models for assessing MAR, particularly MAR techniques that directly interact with the unsaturated zone, such as surface spreading, in-channel modifications, and subsurface recharge via wells, shafts, and boreholes. This is relevant for system design and evaluating impacts on both the vadose zone and underlying groundwater. At regional scales, the vadose zone remains a key connector between the surface and groundwater, and should be taken into account, as it contributes largely to recharge, and evapotranspiration (Stewart et al., 2025). However, extending detailed vadose-zone representations to large-scale models is challenging due to data and computational constraints, in addition to scaling issues particular to these processes (Harter et al., 2004).

Similar challenges apply to other physically-based models (e.g., groundwater flow and transport models), since they often provide a lower degree of abstraction in representing hydrogeological processes, which in turn requires extensive parameterization and computational resources at regional scales or for long-term temporal analysis. These limitations are less restrictive when high-quality data and sufficient computational resources are available. Focusing on the integrated hydrological and anthropogenic water system, numerical distributed groundwater models often consider the components of the anthropogenic system as exogenous factors to the modeled groundwater system and MAR setting (Banton and Klisch, 2007; Jovanovic et al., 2017), which could restrict the model's ability to simulate dynamic interactions between these subsystems and allowing an integrated representation of MAR systems. Therefore, the dynamics of urban-sourced and urban-serving MAR can be misrepresented when only process-based models of the hydrological system are applied for the analysis.

### 3.2. *Lumped/semi-distributed water balance modeling*

Water balance models have been used to improve the understanding of the variables in the hydrological system, and parameterize their relationships, useful for investigating a range of hydrological problems (Xu and Singh, 1998). In these models, the level of complexity and parametrization strongly depends on the objective of the study, and data availability. In the context of water resources management, a water balance can indicate the water flows into the catchment including upstream inflow, imported water sources, etc., which are primarily the

[1] Note that "abstraction" here differs from its use in water resources, where it refers to groundwater extraction.

**Table 1**
Classification and description of model-based regional MAR studies according to the criteria in Sec. 2.2.

| Modeling methodologies | | References | Treatment of space | | | Treatment of time | | | Endogenous subsystems | | | | | Model objective | MAR phase | Source water |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Lumped | Semi-distributed | Distributed | Steady-state | Aggregate values | Dynamic | GW | SW | AW | Agr | SE | | | |
| Process-based models | GW flow models | Banton and Klisch (2007) | | | ☑ | | | short-term | ✓ | ✓ | | | | GWM | PA | SW |
| | | Jovanovic et al. (2017) | | | ☑ | | | medium-term | ✓ | ✓ | | | | GWM | PA | StW, TWW |
| | | Pavelic et al. (2004) | | | ☑ | | | medium-term | ✓ | | | | | DES, GCP | DES | StW, TWW |
| | | S. Liu et al. (2024) | | | ☑ | | | medium-term | ✓ | | | | | GWM | PA | SW |
| | | Zakir-Hassan et al. (2025) | | | ☑ | | | medium-term | ✓ | ✓ | | | | GWM | PL | StW |
| | | Scanlon et al. (2025) | | | ☑ | | | long-term | ✓ | ✓ | | | | GWM | PA | SW, StW, TWW |
| | Water balance models | Lindhe et al. (2020) | ☑ | | | | | medium-term | ✓ | ✓ | ✓ | | | Dem | PL | SW |
| | | Glendenninga and Vervoort (2011) | | ☑ | | | medium-term | | ✓ | ✓ | | ✓ | | GWM-Dem | PA | RW |
| | Water Allocation models | Clark et al. (2015) | | ☑ | ☑ | | | long-term | ✓ | ✓ | ✓ | | | Dem | PL | TWW |
| | | Gómez et al. (2006) | | ☑ | ☑ | | | short-term | ✓ | ✓ | ✓ | ✓ | | GWM-Dem | PL | SW |
| | | Berredjem et al. (2023) | ☑ | | ☑ | | | long-term | ✓ | ✓ | ✓ | ✓ | ✓ | Dem | – | ND |
| Holistic models | SDM | Zanjanian et al. (2024)* | ☑ | | | | | | ✓ | | ✓ | ✓ | ✓ | GWM-Dem | – | – |
| | | Balali and Viaggi (2015)* | ☑ | | | | medium-term | | ✓ | ✓ | ✓ | ✓ | ✓ | GWM | – | – |
| | | Bates et al. (2019)* | ☑ | | | | medium-term | | ✓ | ✓ | | ✓ | ✓ | GWM | – | – |
| | | Niazi et al. (2014) | | ☑ | | | | long-term | ✓ | ✓ | | ✓ | | GWM-Dem | PL | SW |
| | | Zhao and Boll (2022); Zhao et al. (2021) | ☑ | | | | | long-term | ✓ | ✓ | ✓ | ✓ | ✓ | GWM-Dem | PL | SW |
| | DBN | Molina et al. (2013)* | ☑ | | | | long-term | | ✓ | | | ✓ | ✓ | GWM | – | – |
| | BN | Sušnik et al. (2013) | ☑ | | | X | | | ✓ | | ✓ | ✓ | ✓ | GWM-Dem | PL | TWW |
| | | Portoghese et al. (2013)* | ☑ | | | | long-term | | ✓ | | | ✓ | ✓ | GWM | – | – |
| Integrated models | SDM-GW model | Chang et al. (2010) | SDM | | GW flow models | | | medium-term | ✓ | ✓ | ✓ | ✓ | | GWM-Dem | PL | SW |
| | SW-GW flow model | Ghasemizade et al. (2019) | | | ☑ | | | long-term | ✓ | ✓ | ✓ | ✓ | | GWM-Dem | PA | StW |
| | Water allocation - GW flow -Hydrological - Geochemical models | Palma et al. (2015) | | | ☑ | | | long-term | ✓ | ✓ | ✓ | ✓ | | GWM-Dem | PL | TWW |
| | Water allocation -GW flow models | Niswonger et al. (2017) | | Water allocation model | GW flow model | | | medium-term | ✓ | ✓ | | ✓ | | GWM-Dem | PL | SW |
| | MF-Onewater | Hanson et al. (2014) | | ☑ | ☑ | | | long-term | ✓ | ✓ | ✓ | ✓ | | GWM-Dem | PL | RW, TWW |
| | Multiple water balance models | Guyennon et al. (2017) | ☑ | ☑ | ☑ | | | long-term | ✓ | | ✓ | ✓ | | GWM-Dem | PL | SW |

(*continued on next page*)

**Table 1** (*continued*)

| Modeling methodologies | References | Treatment of space | | | Treatment of time | | | Endogenous subsystems | | | | | Model objective | MAR phase | Source water |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Lumped | Semi-distributed | Distributed | Steady-state | Aggregate values | Dynamic | GW | SW | AW | Agr | SE | | | |
| ABM-GW models | Bolton and Berglund (2023) | | ABM (household scale) | GW flow models | | | medium-term | ✓ | | | ✓ | ✓ | GWM-Dem | PL | RW |
| SDM-AI | Secci et al. (2024)* | SDM | | GW flow models/AI | | | long- & medium-term | ✓ | ✓ | | ✓ | ✓ | GWM | PL | – |
| WSIMOD | Liu et al. (2023)* | ☑ | ☑ | | | | medium-term | ✓ | ✓ | | ✓ | | GWM-Dem | PL | – |

Abbreviations: GW = Groundwater; SW= Surface water; AW = Anthropogenic Water-including drinking water production and/or demand, wastewater treatment plants, industry, urban use, hydropower use; Agr = Agricultural demand; SE = Socio-economical subsystem. GWM = Groundwater Management; Dem = Demand satisfaction; GCP=Geochemical processes. PL=Planning; DES = Design; PA=Performance assessment. RW= Rainwater; SW= Surface water; StW= Storm water; TWW = Treated wastewater. ND= Not determined. *indicates cases where other groundwater interventions were studied. The analysis horizon is specified as near real-time (minutes to several days), short-term (weeks to months), medium-term (1–30 years), and long-term (30–100 years).

sources of water supply. System outflows may consist of surface water, in addition to the different water demands. Therefore, these models can provide a holistic quantification of both hydrological and anthropogenic components of the water system and evaluate temporal and spatial patterns of water supply and demand, whether represented in lumped, or semi-lumped formats. They can support the evaluation of changes in flow patterns following the implementation of interventions such as MAR.

In addition to case-specific models developed based on the water balance concept (Glendenninga and Vervoort, 2011; Lindhe et al., 2020), some commonly known PC-based water allocation and planning tools such as WEAP (Stockholm Environment Institute, 2025), AQUATOOL (https://aquatool.webs.upv.es) and Water Community Resource Evaluation and Simulation System (WaterCress) (CSIRO Land and Water, 2025) have also been used to assess the potential of MAR applications as a reliable supply source in the catchments (Berredjem et al., 2023; Clark et al., 2015; Gómez et al., 2006; Simonovic, 2002). They often represent different components of the system, such as catchment hydrology, storage elements, diversions, treatment centers, waste flows and customer demands. These models also include features for economic analysis.

### 3.3. System dynamics modeling

System Dynamics Modeling (SDM) is a methodology rooted in systems theory, appropriate for understanding non-linear behavior of complex systems (Simonovic, 2020). It focuses on how system behavior emerges from internal structures and functions (Forrester, 1961; Sterman, 2000), assessing how changes within endogenous elements influence system-wide dynamics (Simonovic, 2002). As a top-down method, SDM relies on causal thinking and feedback loops (balancing or reinforcing) to model system dynamics. A key step is creating a Causal Loop Diagram (CLD), a qualitative, expert-informed tool that maps feedback and cause-effect relationships (Mirchi et al., 2012), which is refined iteratively as system understanding improves (Sušnik et al., 2012).

The quantitative simulation model is constructed by translating the CLD into interconnected components (*stocks)*, linked together with *flows* and both influenced by *auxiliaries* (parameters). In this conceptualization, stocks represent accumulated state variables (e.g., water) driven by inflows and outflows of quantities over time, with system dynamics simulated using ordinary differential equations. SDM is generally not well-suited for spatial representation of system components, since it uses aggregated (lumped) stocks that represent system behavior over a study region. However, in some cases, SD has been enhanced though combination with GIS tools to incorporate spatial representation (Neuwirth et al., 2015; Niazi et al., 2014). Alternatively, semi-lumped configurations within SD structures have been developed to simulate groundwater levels more efficiently, while allowing representation of nonlinearities from other components of the water system (Roach and Tidwell, 2009). SDM can flexibly integrate physical (e.g., hydrological, environmental) and non-physical (e.g., social, economic) subsystems (Phan et al., 2021) as endogenous elements of a unified model, enabling holistic assessment. This methodology has been applied to a range of environmental and water resource issues (Phan et al., 2021), including groundwater management cases (Afruzi et al., 2021), though less frequently, such as assessments of how MAR (Niazi et al., 2014; Zhao et al., 2021), water pricing and water saving policies (Balali and Viaggi, 2015; Zanjanian et al., 2024), and irrigation constraints (Secci et al., 2024) affect groundwater availability and supply-demand balance. It allows simultaneous analysis of objectives, revealing trade-offs and feedbacks often missed when components are modeled separately. In MAR planning, the inclusion of feedback processes is important, especially when addressing long-term sustainability and resilience of the water system (Zhao and Boll, 2022; Zhou et al., 2025). Emergence of behaviors from interacting feedback loops is one of the features of SDMs which allows the investigation of process dominance (reinforcing or balancing the overall system state) in time.

### 3.4. Agent-based models

Agent Based Models (ABMs) are bottom-up approaches (Berglund, 2015), where behavior at system-level emerges from the interaction of low-level, individual components (agents) with each other and with a shared environment. Agents update their state characteristics based on rules of behavior at each time step, based on the interaction with other agents, or towards satisfying a goal related to the shared environment.

This methodology is useful for studying feedbacks between social (e.g. hierarchical decisions, learning, the dynamics of multiple stakeholders) and physical systems (hydrological and urban system). Similar to SDMs, ABMs are often used to facilitate system understanding across a range of parameter settings and to generate scenario-based insights. However, both ABMs and SDMs share a common limitation in precise, point-in-time predictions (Berglund, 2015) particularly in systems involving human behavior and decision-making. Therefore, applying ABMs in groundwater management studies requires data on how people make decisions, adapt, and coordinate, as these behaviors influence system states (e.g., groundwater availability). Such data are essential for calibrating and validating the models for predictive applications. Moreover, ABMs allow for spatial representation through agent characterization. Recent application of ABMs to groundwater systems has increased (Canales et al., 2024), due to the importance of assessing decision-making on groundwater systems such as decentralized (household level) injection of harvested rainwater for MAR (Bolton and Berglund, 2023). These approaches can be used in combination with other models of the hydrogeological system (See Sec. 3.3), to represent the feedbacks between human behavior and groundwater conditions at each time step.

### 3.5. Bayesian networks

Bayesian Networks (BNs) (Pearl, 1988) have been widely used for knowledge representation and reasoning of complex systems under uncertainty. They consist of directed acyclic graphs (DAGs), where nodes represent variables and edges indicate dependencies. These dependencies are quantified using Conditional Probability Tables (CPTs), which support probabilistic inference of variable states. DAGs and CPTs can be build using stakeholders and expert knowledge, empirical data, simulations, or a combination of these (Phan et al., 2016). Unlike SDM and ABM methods, BNs are not inherently designed to capture dynamic feedback loops, and since they represent system state under stationary conditions, they are not well suited for capturing the dynamics of a system over time. On the other hand, the ability of BNs to effectively represent stochasticity in systems is what makes them particularly valuable tools in the context of water resource management and environmental problems. In particular, Sušnik et al. (2013) compare the applicability of this methodology and SDM for water management through artificial recharge of treated effluent combined with demand-side policies. The study highlights their complementary roles in analyzing different aspects of system-wide policy impacts on a stressed aquifer.

To allow BNs to capture transient system states, Dynamic Bayesian Networks (DBNs) (Kjærulff, 1995) were introduced, which rely on time slicing, in which networks representing multiple time domains are linked together. This enables the representation of the evolution of conditional probabilities (system stochastic outcomes) over the time period of analysis. For example, Molina et al. (2013) applied this methodology to assess the temporal evolution of a stressed groundwater system under climate change impacts. However, one disadvantage of BNs, similar to SDMs, is that the model structure can become overly complex, which adds to the need for more data to formulate the CPTs (Govender et al., 2022; Phan et al., 2016). Moreover, the probabilities and dependencies are constrained by the quality and availability of the data used for their calculation.

### 3.6. Integrated models (hybrid methodologies)

Another approach for modeling complex systems is coupling different modeling methodologies to create an integrated representation of the system. This either includes (i) the integration of different subsystem models together into a unified model (Kelly et al., 2013), or (ii) the combination of different approaches (SDM, ABM, BNs, process-based models of each subsystem) or other modeling methodologies such as Machine Learning (ML) models (Tripathy and Mishra, 2024), leveraging their respective strengths. Model integration can be either achieved through loose coupling, where outputs from one model feed sequentially into another without feedback (Bolton and Berglund, 2023), or tight coupling, where models exchange inputs and outputs within each time step through feedback loops (Boyce et al., 2020).

Integrated models are generally highly complex, reflecting the complexity of the sub-models from which they are constructed. This adds to their computational demand and data requirements. Integrated models enable the coupling of existing subsystem models, simplifying setup by avoiding the need to build from scratch. This is especially useful in loosely coupled models, where sub-models can be calibrated and validated independently. However, there is ongoing debate about how errors from individual sub-models propagate once integrated (Bach et al., 2014). This type of integrated modeling allows for multi-scale representation of processes within the integrated water system.

An example of an integrated model is MODFLOW One-Water Hydrologic Flow Model (MF-OWHM) (Boyce et al., 2020), a process-based distributed model for demand-driven, supply-constrained conjunctive use. It supports regional analysis of MAR (Hanson et al., 2014), by simulating infiltration, recharge rates, groundwater levels, and water availability response to recharge strategies, within a unified system. The authors emphasize that this integrated approach was essential for analyzing coupled flows that would be difficult to estimate otherwise. In another study, Bolton and Berglund (2023) combined a groundwater flow model with an agent-based model to evaluate a micro-trading rainwater program for urban aquifer recharge. Consumers and prosumers interacted with a MODFLOW model via negative and positive pumping rates, respectively, simulating the program's impact on groundwater levels. L. Liu et al. (2024) used the Water Systems Integrated Modeling Framework (WSIMOD) for flux tracking in groundwater for abstraction management. WSIMOD is a modeling framework for integrated water management in terms of water quality and quantity problems (Dobson et al., 2023) and it simulates interactions across water system components (modeled as nodes connected by arcs conveying water and pollutants) addressing both quantity and quality. Feedbacks are incorporated via data exchange or rule-based triggers. WSIMOD's parsimonious representation and flexible architecture can allow for the integration of both anthropogenic and hydrological systems.

### 3.7. Integration with machine learning approaches

Machine learning (ML) methodologies are used to identify patterns and make predictions based on empirical data (Ahmed et al., 2024). Some ML methods are used to learn the relationships between input variables (e.g., rainfall, soil-types, pumping rates) and outputs (e.g., groundwater levels, river discharges). As such, they are powerful tools to study complex non-linear relationships in datasets, without prior knowledge of underlying physical laws. Contrary to physically-based models which require high quality estimates for a limited number of parameters (which may be spatially and/or temporally varying, adding to the data requirements), ML methods (especially the more complex ones) can tolerate lower quality data, although needed in greater numbers. The physically-based models encapsulate system behavior in theoretically sound equations, which are fundamentally correct if properly chosen; whereas ML models depend entirely on having seen sufficient training data. These differences also highlight the various sources and types of uncertainty inherent in each modeling approach.

ML methodologies (a key class of data-driven approaches) have become valuable tools in water resources disciplines (Tripathy and Mishra, 2024) and groundwater management (Rajaeea et al., 2019). ML methodologies have shown promise in evaluating MAR performance, particularly in addressing local-scale challenges (Sheik et al., 2024). This includes prediction of groundwater levels (Bai and Tahmasebi, 2022; Dai et al., 2024; Fernandes et al., 2024; Rajaeea et al., 2019), and clogging (Chew et al., 2024).

In the regional context, ML methods can be combined with holistic approaches to improve the representation of the subsystems, while allowing representation of system-level behavior and dynamics. For example, Secci et al. (2024) combined the use of SDM, and a surrogate ML model (i.e., a simplified, data-driven approximation of a complex physical model) for a fast calculation of groundwater levels. Complementary to this model, effects of system-wide conditions and constraints in irrigation management and pumping restrictions can be assessed using the SDM.

Recent studies have shown growing interest in hybrid methodologies, including combinations of data-driven and process-based approaches (Schweidtmann et al., 2024), as well as integration of different machine learning techniques and other statistical methods (Ahmed et al., 2024). These hybrid approaches have been employed to improve prediction accuracy, provide explainability, and improve generalization (Tripathy and Mishra, 2024). Moreover, the integration of ML methods and process-based approaches provides better interpretability to model performance, which is one of the shortcomings of ML approaches. Despite the advantages of machine learning methods in hydrogeological contexts, they remain highly dependent on data availability. This means that more complex models typically require larger and more diverse datasets. Additionally, overfitting, where a model becomes overly tailored to the training data, capturing noise or irrelevant patterns, poses a significant risk, potentially compromising the model's performance on unseen or future data. In addition, these models are often constrained by their low capacity to extrapolate beyond the training data, posing challenges in transient and non-stationary environmental systems (Bai and Tahmasebi, 2022), especially in hydrological and anthropogenic water systems under changing climate and socio-economic conditions.

### 3.8. Examples in literature

Table 1 presents 22 examples of model-based analyses of MAR applied in regional contexts. These examples are categorized according to the modeling methodologies described in the previous section further grouped into process-based models, holistic models and integrated models. For each case, the table provides information on the objective of the analysis, the subsystems included in the models (as outlined in Fig. 1), and the phase of the MAR project addressed; planning, design, operation, or performance assessment. Additionally, the spatial and temporal scales of the modeling approaches are also included. Furthermore, the information on the source water used for aquifer recharge is presented in the table, which represents whether or not the model-based analysis considers the source variability, an aspect that is essential especially in urban-sourced MAR.

Table 1 presents various regional, large-scale MAR examples assessed using groundwater flow models. Although this review focuses on model-based analyses that incorporate cross-sectoral components of MAR, these examples are included to offer a comparative framework alongside more holistic and integrated modeling studies. We should further mention that the number of examples provided for each modeling approach is not intended to reflect their overall prevalence or frequency of application. Rather, they were selected to illustrate how each approach is applied in practice.

We can observe that regional-scale integrated/holistic modeling studies that focus on water quantity aspects of MAR and treated wastewater as the source water remain limited. This was notable even though the search terms explicitly included *treated wastewater, water reuse, and reclaimed water* in the context of MAR and model-based regional analyses. This observed gap can be partly attributed to regulatory constraints. In many countries, strict regulations govern the direct or indirect use of reclaimed water, which may limit its adoption at a regional scale, discouraging its large-scale implementation. However, treated wastewater sources have been combined together with other sources of water for replenishment projects (Hanson et al., 2014; Jovanovic et al., 2017; Pavelic et al., 2004; Scanlon et al., 2025).

Process-based, distributed groundwater models are commonly used in regional applications, but they usually represent the hydrological side in detail and keep anthropogenic subsystems exogenous or simplified, even in cases where the source water is from the anthropogenic system (Zakir-Hassan et al., 2025). That limits feedbacks between human water use and groundwater in a single run.

We can also observe that despite the lower flexibility of water balance and allocation models in explicitly representing feedbacks, they have been applied in assessment of MAR with surface water (Lindhe et al., 2020) or stormwater (Glendenninga and Vervoort, 2011), since they implicitly consider feedbacks between surface and groundwater systems, although with a higher degree of abstraction in comparison to coupled surface-groundwater models (Niswonger et al., 2017). This may also reflect the MAR community's greater familiarity with these models. In addition to the examples of model-based regional MAR, Table 1 includes studies (7 in total, marked with an asterisk) where integrated/holistic modeling approaches have been successfully used in other groundwater interventions such as water pricing (Balali and Viaggi, 2015), domestic water-saving policies (Zanjanian et al., 2024), nature-based solutions (Liu et al., 2023), and irrigation policies (Molina et al., 2013; Portoghese et al., 2013; Secci et al., 2024). Analyzing the water quantity aspects of these interventions using such models is particularly relevant, since similar to MAR, they impact multiple components of the integrated hydrological and anthropogenic water system. These models have proven valuable in simulating medium- and long-term, system-wide effects, offering insights that can similarly inform sustainable application of MAR strategies.

The classification in Table 1 does not include MAR type (e.g. based on the classification by Sprenger et al. (2017)) because, at regional scales, model selection is primarily driven by system-level objectives, such as contribution to groundwater management, supply-demand satisfaction, and interaction with other components of the integrated water system (Fig. 1), rather than the operational details of a specific MAR scheme. This contrasts with local or site-specific studies, where MAR type strongly influences the choice of process-based models due to differences in infiltration dynamics, recharge mechanisms, and operational constraints. Nevertheless, when practitioners aim for integrated modeling of the regional system, site-scale process models can be coupled with surface water, urban drainage, or allocation models to capture feedbacks and assess long-term sustainability under varying scenarios (Ghasemizade et al., 2019; Palma et al., 2015). Including non-MAR examples in Table 1 therefore serves as a guide, illustrating both the need and feasibility of integrated modeling approaches for MAR planning and assessment, particularly in large-scale cases.

Furthermore, the reviewed studies indicate that at the regional scale, physically-based distributed groundwater models are primarily applied for analyses up to medium-term time horizons (Fig. 3). This is understandable, given their often high computational demands. While long-term analyses using these models are also performed (Scanlon et al., 2025), they typically explore a limited range of future scenarios. However, if sufficient computational resources are available, a broader set of scenarios can, of course, be simulated. Similarly, ML models are used for near real-time, short-, and medium-term analyses. As discussed in Sec. 3.4., these models struggle with extrapolations, which poses challenges for long-term simulations, even when large historical timeseries data is available. Integrated models, consisting of process-based or ML models

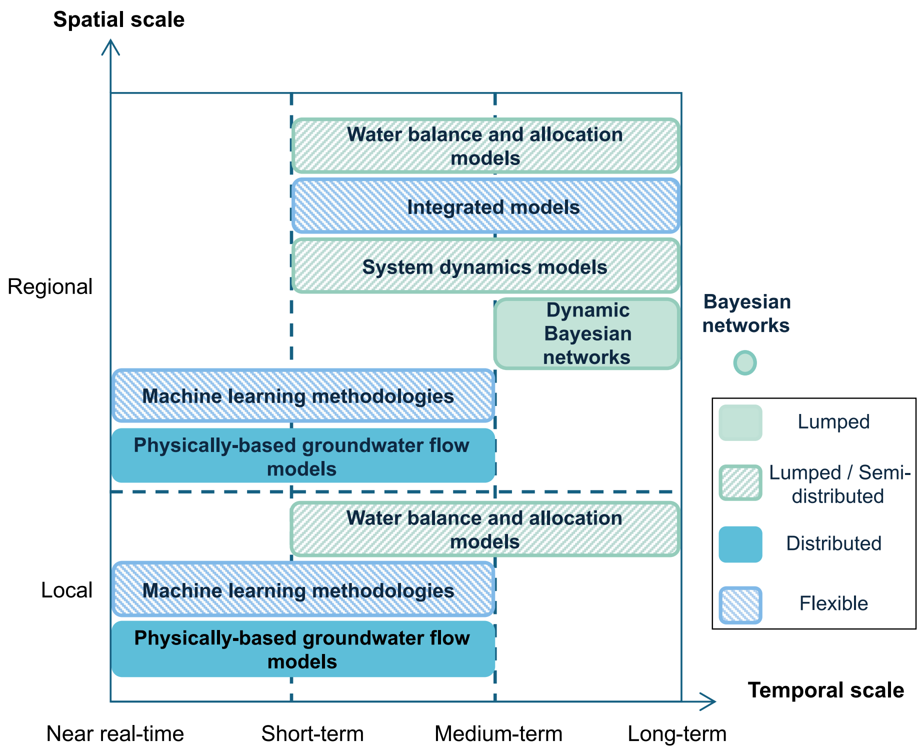


**Fig. 3.** Comparison of modeling approaches for assessing MAR in relation to regional water quantity challenges. The figure illustrates the spatial (local to regional; lumped, semi-distributed, or distributed) and temporal (short-to long-term) scales at which the modeling approaches were applied in the reviewed studies. Positions represent typical applications observed in the selected literature, not the full theoretical range of each approach. Bayesian Networks are shown outside the temporal range due to their non-temporal structure. System dynamics models have primarily been used for lumped representations, but examples of semi-distributed cases also exit in literature. Integrated models are shown within regional scales and applied at longer time scales, based on their use in the reviewed studies, although they can be applied across broader spatial and temporal scales.

of subsystems involved in the integrated water system (as illustrated in Fig. 1), SDMs and DBNs, are often used in regional studies and for medium-to long-term planning. Their lumped or semi-distributed feature makes it more feasible to simulate a wide range of future scenarios and incorporate nonlinearities across the broader system. These models enable analysis of the bulk components of the water system in an aggregated manner. However, it is important to remain aware of the types of feedback mechanisms they can (or cannot) represent.

## 4. Discussion

### *4.1. Comparison of the integrated and holistic modeling approaches*

Table 2 compares the strengths and limitations of the modeling approaches used for the assessment of MAR regional objectives, with regards to the temporal and spatial scale and resolution, their flexibility to incorporate feedbacks, and model complexity. Such a comparison allows for a more informed decision for the choice of appropriate methodologies, fit to the specific type of application and goal. In addition, a comparative view of each approach's strengths reveals opportunities for integration and strategic coupling of the different methods to improve predictive capabilities, while offering deeper insights into system behavior.

For instance, ML models can significantly improve computational time in groundwater level predictions resulting from MAR implementation (Fernandes et al., 2024), enabling exploration of multiple scenarios often constrained by physically-based models. Although efforts have been made to couple multiple subsystem models to better capture interconnections and feedbacks (Palma et al., 2015), these approaches are computationally expensive (Wardropper and Brookfield, 2022). This is due to their low level of abstraction in representing subsystems, which increases the complexity of iteratively running integrated models. Machine-learning approaches that bypass the complexities of distributed groundwater models while still properly representing groundwater dynamics (Miro et al., 2021) can significantly improve integrated modeling (Shen, 2018).

In addition, attempts have been made in coupling holistic modeling techniques with more detailed subsystem (component) models. For instance, coupling of an SD model and a groundwater flow model (Chang et al., 2010) helped improve groundwater recharge estimation fed to the SD model. This type of integrated approach allows assessing the performance and long-term effects of different water management alternatives including MAR, both on groundwater systems and on supply reliability. Bayesian networks offer a holistic modeling approach, valuable for stochastic estimations (Table 2). However, their complexity can limit interpretation and application. Integrating them with machine-learning approaches can enhance estimation of the conditional probabilities (Moradi et al., 2022).

The different modeling approaches assessed can provide complementary perspectives for analyzing regional hydrological and anthropogenic water systems (Secci et al., 2024; Sušnik et al., 2013) and evaluating MAR as part of that system. However, examples which apply multiple methodologies in a comparative way are scarce and increased application of these methodologies can enhance their effectiveness and informed utilization.

We should note that the strengths and limitations summarized in Table 2 reflect patterns observed in the reviewed literature rather than universal facts about the modeling methodologies. Some of the characteristics discussed are context-dependent and influenced by factors such as data availability, computational resources, and system complexity. To address this uncertainty, we explicitly note that these statements should be interpreted as patterns in the reviewed examples rather than absolute properties. Therefore, the comparative insights in Table 2 should be considered within the scope of these reviewed

**Table 2**
Strengths and limitations of diverse modeling methodologies in supporting regional objectives during MAR planning and assessment, based on the examples in literature.

| Modeling Methods | Strengths | Limitations |
|---|---|---|
| Process-based groundwater models | • Grounded in physical laws<br>• Flexible in temporal and spatial details<br>• Familiar to the hydrogeological community<br>• Facilitates interpretability and systems understanding (white-box models)<br>• Suitable for exploring terrae incognitae (beyond known system conditions, such as climate change impacts) | • Model parameterization dependent on high quality and detailed hydrogeological and stratigraphical data<br>• Often computationally demanding (for multiple scenario analysis and long-term runs)<br>• Limited to groundwater system processes |
| Machine learning models for groundwater prediction | • Can offer faster computation than numerical groundwater models (especially for scenario exploration)<br>• May provide enhanced predictive capability compared to process-driven models under data-rich conditions | • Data hungry<br>• Poor extrapolation capability (long-term predictions such as non-stationary climatic conditions)<br>• Often lack interpretability (black-box models) |
| Integrated surface and groundwater flow models | • Integration of surface water and groundwater dynamics<br>• Representation of feedbacks between surface and subsurface flows (especially for MAR using surface water and stormwater) | • Analysis is limited to hydrological domain<br>• Requires quality data for both surface and groundwater model parameterization<br>• High computational cost to evaluate multiple scenarios quickly |
| Water Balance models | • Adaptable abstraction degree, depending on data availability<br>• Flexible for incorporating anthropogenic water demands for water accounting<br>• Capable of including feedbacks and delays by using customized equations | • Process parameterization is often kept simple, often lumped (limited representation of spatial heterogeneity)<br>• Limited representation of hydrological system, especially groundwater flow dynamics |
| Water Allocation models | • Simplified and efficient accounting of supply availability, reliability, trade-offs among multiple demands<br>• Suitable for water allocation planning | • Limited representation of hydrological system, especially groundwater flow dynamics (needs coupling with domain models)<br>• Includes implicit feedbacks (explicit feedbacks need to be implemented using modular or custom equations) |
| System Dynamics models | • Holistic representation of the hydrological and anthropogenic water systems, socioeconomic, and infrastructure components<br>• Captures feedback loops, delays and nonlinear behaviors<br>• Efficient for long-term scenario simulation<br>• Suitable for strategic planning<br>• Useful for analysis of hidden behaviors emerging due to the interaction of all model components | • Lumped representation of the system (lumped but can be integrated to semi-distributed structure)<br>• Lacks spatial aspect<br>• Model structure can become overly complex, increasing model parameters<br>• Challenging representation of hydrogeological processes |
| Bayesian Networks | • Appropriate for quantifying uncertainties (stochastic nature), and variabilities in all system variables<br>• Capable of incorporating qualitative data (expert opinion especially when quantitative data is scarce), socioeconomic, and infrastructure components<br>• Suitable for strategic planning | • Lumped representation of system components (but can handle spatial aspects indirectly)<br>• Limited capacity in handling dynamic processes- temporal detail<br>• No feedback representation<br>• Limited physical process representation<br>• Model structure can become overly complex |
| Integrated subsystem models | • Realization of integrated modeling through coupling of existing models<br>• Providing multi-scale system representation<br>• Possibility to incorporate feedbacks (between modeled components) | • High computational demand (for multiple scenario analysis and long-term runs)<br>• Requires high model parameterization<br>• Complexity of coupling multiple models (with different spatial and/or temporal resolutions) |

examples. In addition, the strengths or limitations of each approach may not occur concurrently; for example, ML models can offer faster computation or enhanced predictive capability under data-rich conditions, but these advantages do not necessarily coincide. Future updates to this collection incorporating additional literature examples could further refine and enhance the insights presented here.

### 4.2. Uncertainty across modeling approaches

Uncertainty is inherent in model-based analyses of MAR measures, and must be addressed to support robust and responsible decision-making (Refsgaard et al., 2007). Uncertainty in MAR modeling ranges from input data, parameter and structural uncertainty to deep uncertainty related to unknown future socio-economic and climate conditions (Lempert et al., 2003; Walker et al., 2013). The temporal scale of the future system that models aim to represent has an influence on the types and magnitudes of uncertainties introduced in the analysis, as longer time horizons often involve greater unpredictability (e.g., future emission scenarios, climate models, and, socio-economic developments such as future groundwater abstraction levels (Mustafa et al., 2019)). As illustrated in Fig. 4, the diversity of modeling approaches, from physically-based models to machine learning, system dynamics and Bayesian networks, introduces varying capacities for uncertainty representation and quantification, with some models better suited for parameter uncertainty, and others for scenario analysis.

Parameter and input uncertainty are universal aspects of all the reviewed modeling methodologies, making robust MAR assessment fundamentally dependent on high-quality data obtained through comprehensive monitoring, field investigations, and careful data selection, aligned with study objectives and project stage. While such practices substantially reduce uncertainty, input and parameter uncertainty is commonly quantified through sensitivity analysis and Monte Carlo-based frameworks, to evaluate the impact of uncertain inputs and parameters on model outputs (Pianosi et al., 2016).

In physically-based models, which are inherently deterministic, scenario analysis (what-if frameworks) allows to consider the influence of external aspects such as abstraction scenarios, or boundary conditions on simulated outputs. Therefore, exploring alternative external conditions, such as pumping/recharge scenarios, helps assess management or climatic impacts. In physically-based models (like MODFLOW), through scenario analysis, one defines the boundary and management alternatives, followed by sensitivity analysis within or across those scenarios to quantify uncertainty effects. In addition, specific to groundwater flow models, uncertainty in the geological interpretation of the subsurface remains a major limitation, often affecting the accuracy of model predictions. This is typically addressed by considering alternative model structures that represent plausible subsurface configurations (Mustafa et al., 2019). Therefore, in regional scales of MAR analysis, this aspect

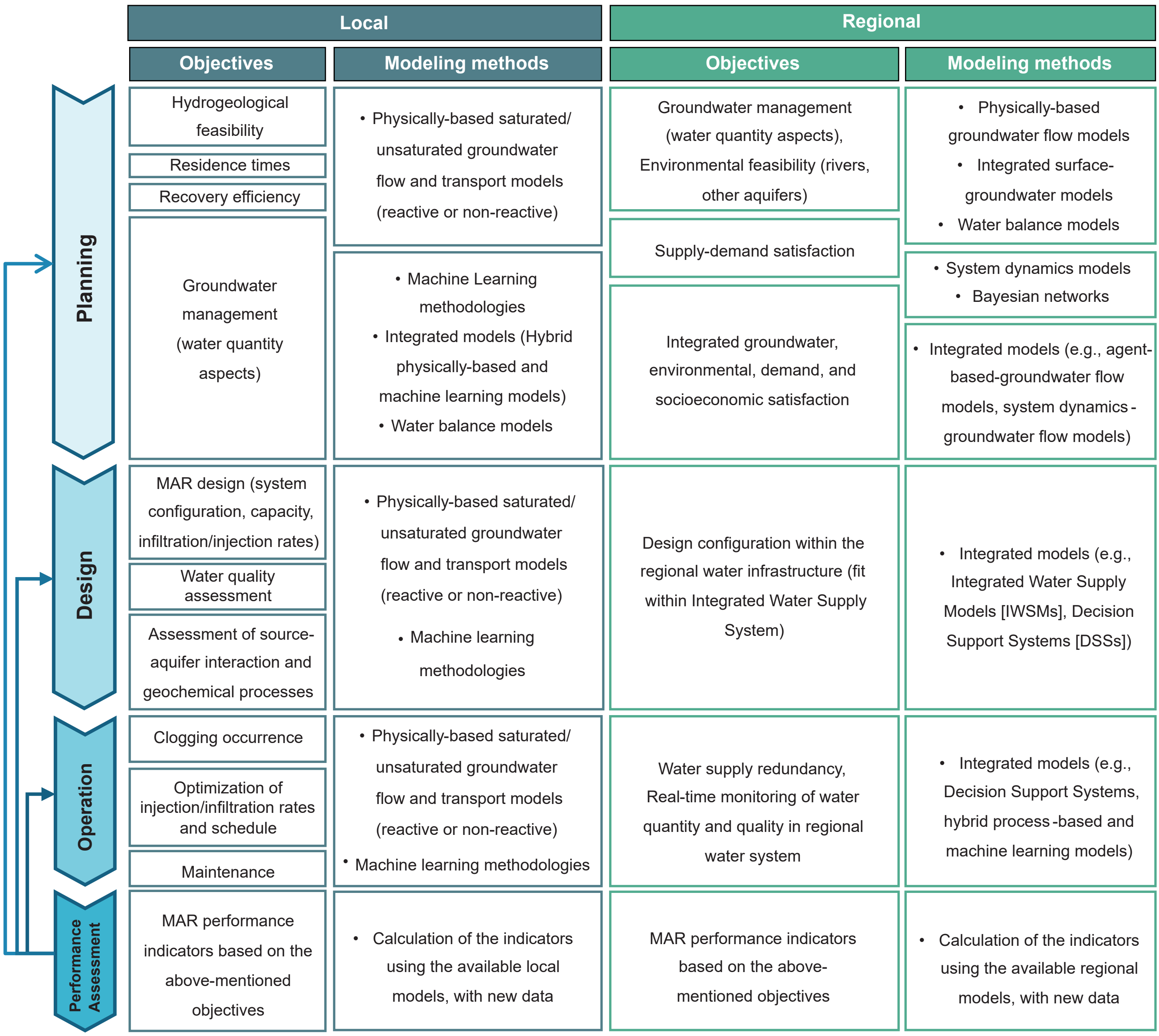


**Fig. 4.** Overview of modeling objectives and methods in MAR studies by phase of analysis and spatial scale, highlighting the connection between project objectives, system characteristics, and the selection of suitable modeling techniques. At local scales, models may include saturated and/or unsaturated flow processes depending on MAR type and site conditions.

needs to be considered when these models are used.

As the complexity of the MAR scheme and the temporal and spatial scales of analysis increase, models are integrated to improve feedback mechanisms within the system under study. For integrated models, uncertainty propagation may amplify or reduce upon integration (Bach et al., 2014), as e.g., more system parameters are introduced in the integrated model (hence, potentially adding to parameter uncertainty), while complex regional system representation is expected to improve upon integration. Various frameworks are available that facilitate mapping this propagation from one model to the other (Kirchner et al., 2021), and introduce quantification frameworks. This is a complex task, especially moving towards integration of multiple modeling frameworks, each with varying schematizations (lumped-distributed subsystem models creating structural uncertainty), scales, parameter uncertainties, and feedback dependencies. These aspects complicate investigation of future scenarios with these models due to computational or methodological barriers.

In holistic modeling approaches such as SDMs, structural uncertainty arises from alternative feedback structures and different levels of model aggregation (e.g., lumped vs. semi-lumped conceptualizations). These aspects should be investigated within the structural uncertainty framework. SDMs are increasingly used in investigation of scenario uncertainty. This is because SDMs are computationally light, so running thousands of scenarios is feasible, which is promising for investigation of uncertain futures e.g. through exploratory modeling approaches (Kwakkel, 2017) applied to SDMs (Kwakkel and Pruyt, 2013).

Bayesian networks are intrinsically probabilistic and explicitly model uncertainty through conditional probability tables (CPTs). Uncertainty in conditional probabilities (arising from limited data, expert judgment, or a priori parameter assumptions), can also be influenced by structural uncertainty in the network. This structural uncertainty can then propagate into parameter uncertainty, affecting the reliability and robustness of the model. Therefore, through uncertainty analysis, the variability of the parameters and the sensitivity of the outputs can be a measure of confidence in the Bayesian network results. In this context, sensitivity analysis methods can be applied to investigate the effect of individual variations to one or more parameter at a time (Ballester-Ripoll and Leonelli, 2025).

Using the range of methodologies for uncertainty assessment (Refsgaard et al., 2007; Walker et al., 2013), the degree of confidence in model-based analyses of the future systems, and the communication of that to decision-makers can be improved. For example, Miro et al. (2021) explored a wide range of plausible future conditions, accounting for deep uncertainties in water management and groundwater systems, which resulted in a “more realistic safety margin” based on a broader view of uncertainty, guiding actionable thresholds for future adaptation. In the same study, due to challenges that e.g., model complexity adds to computational demand in model runs, they implement ML approaches to facilitate exploration of the uncertainty space.

We emphasize the need to explicitly incorporate uncertainty analysis in model-based MAR studies to improve the robustness and relevance of model outcomes for decision-making. A practical starting point is the development of an Uncertainty Framework Table (UFT) (Kirchner et al., 2021), that maps sources and pathways of uncertainty, from inputs through model processes to outputs. This can be followed by adoption of quantification approaches that align with the chosen modeling methodology and the specific uncertainty sources identified, as briefly mentioned in this section.

### 4.3. Water quality

While the primary focus of this review is on water quantity, it is important to acknowledge the significance of water quality aspects in MAR project planning and assessment (Vanderzalm et al., 2022). In particular in local studies, solute transport or reactive transport models have been applied to assess risks associated with introducing external source water into ambient groundwater, as well as its interactions with the aquifer matrix (Sun et al., 2020) or MAR’s potential to mitigate regional groundwater quality deterioration (Guo et al., 2023; Sitek et al., 2025). In addition, ML approaches can facilitate the prediction of water quality and geochemical processes in groundwater systems (Haggerty et al., 2023).

In large-scale studies, focusing on cross-sectoral impacts of MAR applications, i.e., on other components of the integrated water system, is a complex task, since it requires large-scale monitoring to evaluate the effects of source water beyond the aquifer system, or the connected surface waters. For example, Negev et al. (2017) traced water sources in a Soil Aquifer Treatment (SAT) system using isotopic analysis along the water-effluent-SAT chain, enabling a simple mixing equation to predict isotopic compositions throughout the regional water system.

We therefore emphasize the importance of system-wide water quality analysis and modeling in large-scale MAR projects and encourage researchers to explore this further. Although beyond the scope of this review, compiling such applications could provide valuable insights for future integrated water management strategies.

### 4.4. A comprehensive picture

In Fig. 4, an overview of modeling objectives and methodologies in MAR studies is provided, categorized by phase of analysis (planning, design, operation, performance assessment) and spatial scale (local to regional). The modeling approaches also reflect these various dimensions, based on the objectives and data availability at each scale. At the local level, physically-based groundwater flow and transport models are used across all MAR phases due to their ability to represent subsurface processes with high spatial and temporal resolution. These models facilitate assessments of hydrogeological feasibility, residence times, recovery efficiency, and operational optimization. While these challenges are broadly relevant across different MAR types, their significance and underlying mechanisms vary by each MAR approach.

To further enhance predictive performance and simulation efficiency, physically-based models may be integrated with machine learning techniques, provided high-quality data are available. This hybrid approach can offer improvements over numerical groundwater models, particularly in complex or data-rich settings. Water balance models also provide a high-level assessment regarding groundwater management priorities (e.g. recharge feasibility, groundwater levels with respect to demands) and changes in the water budget. Beyond the initial planning, design, and operational phases, the performance assessment of a MAR project is then complemented by key performance indicators (KPIs) at both local and regional scales. These guide adjustments to system design and operational strategies, and based on system performance indicators, efforts for upscaling and replicability of MAR can emerge.

At the regional scale, modeling shifts toward integrated approaches that address broader planning and design objectives, which are relevant across all MAR types. These include water allocation models, system dynamics models, and Bayesian networks, which can incorporate socio-economic and environmental factors, integrating hydrological and anthropogenic water systems. Furthermore, coupling multiple modeling methodologies or multiple subsystem models allows for the investigation of regional effects, while providing various levels of information. For design purposes, MAR is often embedded within integrated water supply systems, for which Decision Support Systems (DSS) and Integrated Water Supply Models (Bach et al., 2014) can be utilized. Furthermore, to assess feasibility of relying on MAR as an additional supply source (increasing supply redundancy) and simulate the real-time state of the regional water system components, coupled models can benefit decision-making at the operational level, which requires more spatiotemporally detailed model outcomes.

## 5. Conclusions, limitations, and future directions

This study was motivated by the ongoing shift in MAR applications from local pilot projects to regional-scale implementations. We first considered the dimensions of MAR cases at the regional scale, focusing on water quantity aspects, and further asked the question: which modeling methodologies are best suited to represent the connections between MAR and the integrated hydrological-anthropogenic water system? When these measures are replicated or scaled up, their interactions with other components of the water system become significant, introducing complexity that cannot be addressed by local-scale approaches alone. To answer this question, we relied on examples in literature, focusing on model-based analyses of regional MAR applications, with a focus on groundwater management and/or in relation to demand satisfaction, while pilot-scale MAR studies without regional/system-level implications were excluded from the reviewed articles.

The classifications presented in this review show trends observed in the selected studies rather than comprehensive characteristics of all MAR applications or modeling approaches. Additionally, this review did not consider a temporal analysis of the evolution or prevalence of different modeling methodologies, which could potentially be valuable for representing research trends over time. Furthermore, the scope of this review was limited to water quantity aspects and studies focusing exclusively on water quality or geochemical processes, as well as non-peer-reviewed sources were excluded. Although this choice was motivated due to the ongoing water quantity challenges in MAR studies, it may have excluded relevant insights from for example, groundwater flow and solute transport modeling studies, or technical reports on MAR applications. We acknowledge that the synthesis on the modeling methodologies is constrained by the availability and reporting quality of the reviewed studies, which may introduce bias in the representation of modeling practices and their applicability to regional MAR contexts. Expanding this review with additional literature in the future could help refine and strengthen the insights presented here.

Based on the literature, the diversity of modeling approaches applied to regional MAR reflects differences in objectives rather than a uniform attempt to represent the entire integrated water system. For example, process-based models are often used to account for groundwater storage changes, by treating demands and sources as static elements, whereas holistic approaches such as system dynamics models explicitly incorporate variability in demand and source availability in combination with the storage changes in the groundwater system and connected surface water to support planning decisions. Water balance models on the other hand provide a general picture of catchment water resources and cover supply-demand portfolios. In these models, focus is less on changing relationships and more on priorities of water allocation. Integrated models of hydrological subsystems and anthropogenic processes are another type of approach that allow investigation of variabilities and focus on the interdependencies. They enable combination of features from multiple models to help with system-level behavior exploration, providing enhanced spatial or process-based representation.

A valid MAR analysis does not always require representation of the full hydrogeological and anthropogenic system; what is critical is aligning the model with the planning horizon, source water variability, hydrological setting, and end-user context. Having these aspects clear, modelers should rely on the differences and similarities between the range of models reviewed here, in order to select suitable models based on their data and computational constraints, while considering the importance of capturing interdependencies and temporal regime changes, especially as large-scale MAR projects reshape both hydrological and anthropogenic systems. In the majority of the studies, this aspect of the regional context is not considered. This review highlights the importance of modeling approaches that facilitate this type of investigation, and establishes criteria that help select appropriate modeling approaches, ensuring choices are informed by the strengths and limitations of each method.

Furthermore, while holistic and integrated models offer promising avenues for considering long-term and cross-sectoral impacts, their adoption remains limited due to computational complexity, data requirements, and challenges in coupling diverse subsystems. Therefore, future research should prioritize hybrid modeling frameworks that combine the strengths of process-based or data-driven models together in an integrated modeling scheme, towards enabling more robust scenario analysis and uncertainty quantification. Parsimonious modeling schemes such as system dynamics models can for example facilitate such integrations. Additionally, policy and planning efforts should leverage integrated models complementary to site-specific studies, to support adaptive MAR strategies that ensure interventions are resilient to climate variability and anthropogenic changes. Addressing these gaps will enhance the relevance and applicability of MAR modeling for sustainable groundwater management.

In addition, future studies should expand the scope of regional-scale MAR analyses to include water quality modeling, or the combination of water quality and quantity modeling, in order to uncover which dimensions of MAR influence system-level sustainability, trade-offs and propagation of effects, particularly in cases involving reclaimed water or complex source water interactions.

## CRediT authorship contribution statement

**Mina Yazdani:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Peter van Thienen:** Writing – review & editing, Validation, Supervision, Conceptualization. **Sija F. Stofberg:** Writing – review & editing, Validation. **Marjolein H.J. van Huijgevoort:** Writing – review & editing, Validation. **Ruud P. Bartholomeus:** Writing – review & editing, Validation, Supervision, Conceptualization.

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## Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Microsoft Copilot in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

## 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.

## Data availability

No data was used for the research described in the article.

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