Modelling Southern Mesopotamia Irrigated Landscapes
How Small-scale Processes Could Contribute to Large-Scale Societal Development

Lang, Dengxiao; Ertsen, Maurits W.

DOI
10.1007/s10816-023-09632-7

Publication date
2023

Document Version
Final published version

Published in
Journal of Archaeological Method and Theory

Journal of Archaeological Method and Theory
https://doi.org/10.1007/s10816-023-09632-7

RESEARCH

Modelling Southern Mesopotamia Irrigated Landscapes: How Small-scale Processes Could Contribute to Large-Scale Societal Development

Dengxiao Lang[1] · Maurits W. Ertsen[1]

Accepted: 6 November 2023

Abstract
Early Southern Mesopotamia shows a complex history of expansion of (irrigated) farming in relation to urban developments and changing landscapes. As a first step to study expanding irrigated farming system, an irrigation-related agent-based model was developed to explore farm(land)s and irrigation systems in relation to decision-making processes, both of farms and their farmlands (an agriculture unit) and collective decision-making processes for irrigation system management—especially sharing water between farms. The decision-making processes include options to move farms, expand the system, or start a new system, as these would be options available for Mesopotamian farmers as well. In this text, we report how model parameters contribute to the generation of various patterns of yields and expansion of farms and system. Additionally, the Gini coefficient (based on yields) is applied to estimate levels of inequality among farmers. Our results show how (1) human decision-making determines the level of influence of and benefits for farms, as well as the overall irrigation system; (2) Gini values effectively capture the degree of inequality in yields among farms based on water availability; and (3) our model is a suitable base for further study, by incorporating additional agents into the irrigation system and expanding the spatial–temporal scales of the irrigated landscapes, to reach a more comprehensive understanding of the evolutionary dynamics of irrigation systems in Southern Mesopotamia.

Keywords Agent-based modelling · Irrigation · Harvest situations · Decision-making · Ancient Mesopotamia

✉ Dengxiao Lang
D.Lang-1@tudelft.nl

[1] Department of Water Resources, Delft University of Technology, Delft 2628 CN, the Netherlands

Published online: 13 December 2023

Introduction

The region of Southern Mesopotamia is generally considered setting for one of the earliest civilisations (Adams, 1981; Rothman, 2004). The landscape of this region comes to the observer as a hydraulic landscape: the history of the region is actually the history of the complex water systems structured by natural and man-made channels, irrigation canals, levees, marshes, and swamps (Altaweel, 2019; Pournelle, 2003; Wilkinson *et al.*, 2015). This history of irrigation management in Southern Mesopotamia needs to be explained as "evolving", in the sense that an earlier, relatively empty landscape with (irrigated) farming most probably being relatively small-scale did transform into a relatively intensively used landscape, with identifiable centralized management of irrigated farming and yields (Adams, 1965; Jacobsen & Adams, 1958; Rost, 2017; Wilkinson & Jotheri, 2016; Wilkinson *et al.*, 2015). Buringh (1960) argues that the first step of irrigation probably involved cutting the river banks, which gradually became a canal system and finally developed into larger irrigation systems on the flood plain. Wilkinson *et al.* (2015) suggest that the management of crevasse splays from the (elevated) channels could act as triggers for artificial cuts providing water to irrigated fields along the levees. Groups of fields would eventually be structured along irrigation canals with associated management by local communities in succeeding generations. Rost (2017) indicates that irrigation management could not only provide subsistence to small communities but also could be the economic basis of states or empires when management was taken over by specific groups. However, an overarching, yet detailed history of irrigation management in a developing irrigated landscape in Southern Mesopotamia has not been written yet. We have good developmental models for earlier periods, we have data from later periods, but we lack a clear trajectory between the two. In this manuscript, we suggest that systematically exploring how irrigation systems could evolve from small-scale to large-scale, from short-term to longer-term, and from independent to collective could build further understanding of the co-development of environmental and socio-political aspects of irrigation systems in ancient Mesopotamia—and as such in other regions and periods as well.

Our own baseline, systematic exploration builds on applying an Agent-Based Model (ABM), as ABMs have shown to be valuable tools to investigate human-water systems, facilitating exploring the intricate interactions between human activities and hydrological characteristics (Alam *et al.*, 2022; Hyun *et al.*, 2019; Streefkerk *et al.*, 2023). Moreover, ABMs have been broadly applied to archaeological research in different sub-fields, including simulating Roman tableware trade procedures and economic history (Brughmans & Poblome, 2016; Brughmans *et al.*, 2019; Carrignon *et al.*, 2020; Graham *et al.*, 2022), modelling networks in archaeology (Collar *et al.*, 2015), exploring the evolution of human language (Ruland *et al.*, 2023), reconstructing past human–environment interactions (Perry & O'Sullivan, 2018), and studying the long-term implications for individuals' preference of local Jerash products (Romanowska *et al.*, 2022), etc. The suitability of ABMs is closely linked to their inherent capability to represent (non)human decision-making in a heterogeneous and flexible manner, accommodating the diverse nature of data available on decision-making outcomes at individual, local, and larger scales (An, 2012; DeAngelis & Diaz, 2019; Murphy *et al*., 2019). ABMs have been recognized as important tools to design, evaluate, and operate water allocation processes (Murphy *et al*., 2015, 2019; Ozik *et al*., 2014). ABMs for irrigation management incorporate various sub-modelling routines, like hydrological and crop models, as well as social factors such as decision-making and interactions, to accurately portray the interplay of natural, economic, and societal dynamics across different temporal and spatial scales (Aghaie *et al*., 2020; Altaweel & Watanabe, 2012; Anthony & Birendra, 2018; Bahrami *et al*., 2022; Hyun *et al*., 2019). Irrigation systems are examples of complex systems, with their changeable stakeholders' decision-making, complicated hydraulic characteristics, and complex water distribution rules among canals and farmers. These features together create interactions between humans and water through the infrastructure, with human actions affecting water availability of other humans, creating reasons for changes in the irrigated landscape by human interventions, that will affect water availability etcetera (Bruijn *et al*., 2023; Davies *et al*., 2014; Ertsen, 2010; Pluchinotta *et al*., 2018). These interactions between human activities and the water system need to be explicitly addressed when studying the development of irrigation systems and irrigated landscapes.

With this in mind, the design logic of our research approach focuses on the dynamic layout of a virtual irrigation system, taking inspiration from the evolving irrigation landscape in Southern Mesopotamia over time. Before the current study, we had already developed the Irrigation-Related Agent-Based Model (IRABM) and the Advance Irrigation-Related Agent-Based Model (AIRABM) (Lang & Ertsen, 2022a, 2022b). IRABM offers a theoretical and methodological framework for examining the interactions among irrigation-related agents and gaining insights into how these interactions can shape water and yield patterns. AIRABM applies a similar design logic to explore the dynamic behaviour of farmlands and yields through decision-making by independent farms as well as collective decision-making processes. Building upon these two models, we have further advanced the model series to the current IRABM^3. In IRABM^3, we maintain the mechanisms for water movement, irrigation scheduling, barley yield response to water supply, farmland dynamics, and decision-making processes at farm and system levels, from the previous two versions. IRABM^3 expands the decision-making process on farm level: next to incorporating choices within the existing canal, the current model includes decision-making in relation to expansion of farming activities in the same irrigation system or by creating a new system. In order to illustrate how dynamics in irrigation systems can emerge from decisions made by heterogeneous agents, three key decisions on two levels of decision-making are included in IRABM^3:

1. Decisions are made on "farms" concerning farmlands dynamics (without specifying which entity exactly makes these decisions), which may lead to
2. Collective decision-making on water distribution between those farms, as in cases with lower yields along the canal, upstream and middle stream farms will gradually lower their gate capacity to distribute water more equally among farms. The result of these adaptations may

3. Trigger a final farm-related or collective decision-making process, based on the realized yields, affecting the overall dynamics of the irrigation system: expansion of farms and/or canals when yields are good or movement of farms when yields are low.

With these three decision processes, offering insights into how human decision-making influenced the development and configuration of the irrigated landscape, we argue that our model presents a useful basic approach to simulate evolutionary patterns of irrigation systems in Southern Mesopotamia on extensive temporal and spatial scales. We will return to this potential in the discussion, after presenting the modelling setup in much more detail further below.

As one of our underlying concepts related to decision-making concerns yields, we added one additional concept to our analysis: the Gini coefficient. Originally, this coefficient was introduced by Gini (1912) to evaluate income inequalities within the realm of economics, and it continues to be commonly utilized in this domain (Campano & Salvatore, 2006; De Maio, 2007; Piketty & Saez, 2014). It is now employed in various research fields, including both modern and ancient contexts. For instance, Harch *et al.* (1997) employed the Gini coefficient to compare bacterial soil communities, Zheng *et al.* (2013) developed the land Gini coefficient (LGC) to evaluate the rationality of land use structure in China, and Sueyoshi *et al.* (2021) investigated technology diffusion inequality among Chinese provinces. The Gini coefficient has also found application in agricultural research for estimating crop yields at various levels (Vesco *et al.*, 2019, 2021). It is also utilized in in archaeology recently, for instance, Kohler *et al.* (2017) utilized a house size Gini coefficient to represent post-Neolithic household wealth and wealth disparities, and studies from Baker (2022) and Basri and Lawrence (2020) have related archaeological evidence of increasing inequality to the Gini coefficient. These applications have demonstrated the universality of the Gini coefficient, and the positive results obtained in evaluating crop yields have further encouraged its continued usage in this field. We did not include the Gini coefficient in the modelling itself (yet), but employed the coefficient to analyse modelled inequalities of barley yields among farms, utilizing annual values of yields and farms' population. This allowed us to examine the spatial–temporal patterns of barley yields among farms and explore the correlation between farms' cooperative tendencies and the Gini coefficient values.

This paper is structured as follows. Section 2 presents the theoretical framework and the analytical approach of IRABM[3]. Section 3 presents the findings obtained from our analysis and discusses the empirical outcomes. Section 4 delves into a comprehensive discussion of the research, examining its implications and potential avenues for further exploration. We will close this paper with Section 5, which summarizes the key findings and highlights the significance and outlook of our research.

Model and Design Description

The current model is built upon the IRABM and AIRABM models, both of which were extensively described in previous papers utilizing the ODD + D (Overview, Design concepts, Details + Decision-Making) protocol (Lang & Ertsen, 2022a, 2022b). Moreover, the Model Design Concepts, the Response of Barley Yields to

Water Supply, the Learning and Memory Behaviour, and the Farm's Decision-making Mechanism remain consistent with the logic presented in the aforementioned papers. In contrast to the previous two versions, which focused on farmland dynamics within one farm (including decisions 1 and 2 mentioned in the Introduction), the current version $IRABM^3$ incorporates both farm and system dynamics, applying all three decisions mentioned. This section will outline how we construct the model system dynamics, specifically the expansion of farms/canals and the movement of farms/canals. The terms used in this paper are listed in Appendix 1.

Southern Mesopotamia

Environmental Background

Modern Southern Mesopotamia has the most fertile agricultural soil in the region, and two thirds of its population is settled in this part of Iraq (Jotheri, 2016). In ancient times, the climate exhibited somewhat higher and more consistent levels of precipitation compared to the current-day conditions. Nevertheless, the contemporary climate still adheres to the prevailing weather patterns of ancient Southern Mesopotamia (Bar-Matthews *et al*., 1999; Lemcke & Sturm, 1997; Rost, 2015). The annual precipitation is less than 100 mm in most years, and rainfall is unevenly distributed throughout the year (Rost, 2015). River water levels are low in September/October and peak just prior to April/May. Southern Mesopotamia lies outside the rain-fed agriculture zone, and it is a semi-arid zone with hot and dry summers but cooler winters; thus, irrigation becomes imperative for agricultural production in this area (Hritz, 2010). It may be worth noting that Southern Mesopotamia would not have been such a dryland in earlier millennia, as the landscape has many swamp-like features (Pournelle, 2003). A gradually drying up of the landscape would have indeed increased reliance on irrigation—a scenario we plan to incorporate in our larger-scale follow-up studies.

Focus on Barley

Although there was a wide range of cultivated grains in ancient Southern Mesopotamia, sufficient evidence indicates that agricultural production was strongly based on winter crops such as barley and wheat (Rost, 2015). We selected barley as our modelling grain because (1) barley is more drought-resistant and tolerant of alkaline soils, and its more productive in drier conditions; and (2) barley played a vital role in political and social uses through its universal distribution in society, including trade (Alexander & Violet, 2012; Edens, 1992; Ellison, 1981; Foldvari & Van Leeuwen, 2012; Helbaek, 1959; Rost, 2015; Smith, 1995). As we will model the development of irrigation system (the irrigated landscape) in Southern Mesopotamia, barley appears to be the perfect crop to start a model. The details of barley growth and yield response to supplied water can be found in Lang and Ertsen (2022a, 2022b).

IRABM³ Design Concepts

The IRABM³ setup has the same initial layout as the AIRABM design shown in Fig. 1: one river feeds 10 farms along one canal, each farm includes 5 potential farmlands that can be planted with the model crop barley. We gave each farmland a constant size of 1 hectare, with farms next to each other sharing similar soils.

The model design concept for IRABM³ is shown in Fig. 2. In addition to the previous two versions, the system dynamics are specifically focused on the expansion of farms/canals and the movement of farms/canals, based on continuous years of harvest situations (the details will be explained in the following sub-section). We do not predefine which entity is making decisions on farms or system, as we focus on the reasons for and results of decisions. Obviously, in future studies such nuances of decision making will need to be included (see Discussion).

Collective Decision-Making on Irrigation Management

Within our latest model, we introduce two primary system dynamics: (1) relocating farms with poor harvests to new areas in—or outside the irrigation system and (2) expanding the irrigation system with extra farms. Both responses can be related to longer term changes in the irrigated landscape, as relocations will mainly increase the number of irrigated areas, whereas expansions would increase the number of irrigation systems and irrigated areas simultaneously (see details in the paragraphs below). These changes in the irrigated landscape entail adjustments in the number of farms or in the size/number of canals. Following these modifications, we take into account water distribution among the canals. To achieve a more equitable distribution of water among canals, our model controls and adjusts the head gate diversion rates based on the ratio of the number of farms along a particular canal to the total number of farms in

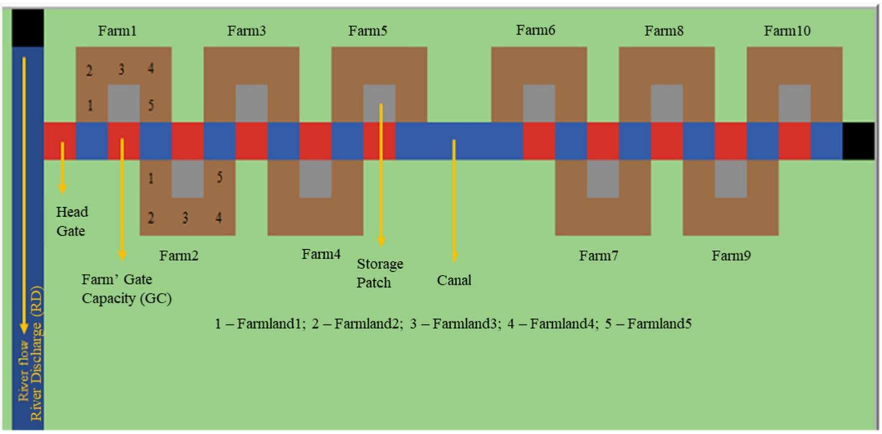

Fig. 1 The initial layout of the modelled irrigation system

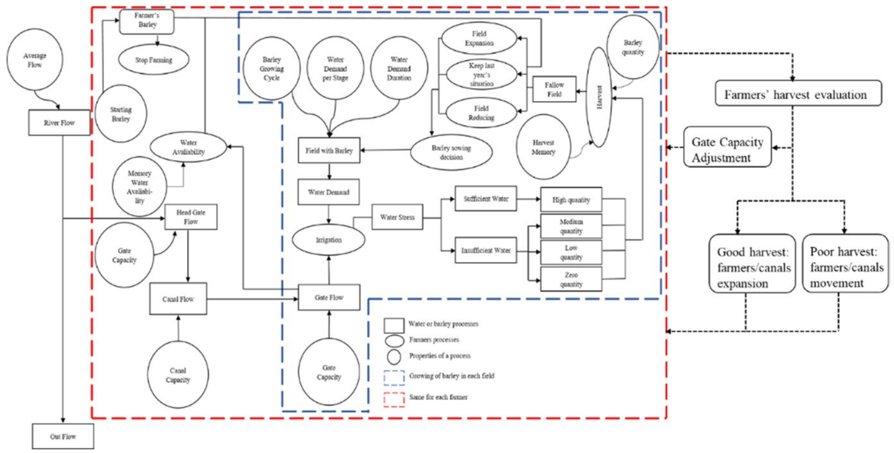

Fig. 2 The overview of the IRABM^3 design concept

the entire system. This ensures that water is distributed more evenly among the various canals in the current model setup—which is obviously a feature that needs further study as well.

System Movement Decision-Making Processes

Irrigation water can be considered "common pool resource", with unequal access to water between upstream and downstream farmers posing a significant challenge in the "irrigation dilemma" when farmers share the common water resource (Albiac *et al*., 2020; Ostrom & Gardner, 1993). Generally, unequal access to water easily causes inequality of crop yields among farmers. With these concepts, we can move to the collective decision-making process which involves the movement of farms and canals in response to poor harvest situation. The initial configuration of our model consists of 10 farms. We define "poor harvest situation" as upstream farms having successfully harvested five farmlands while downstream farms have fewer than three harvested farmlands (for details on these farmlands' dynamics in the model see Lang and Ertsen (2022a)). In other words, we consider barley yield inequality between farms as key for decisions on movement and/or expansion. When such a poor harvest situation arises and continues for at least five years, the model system decision procedure contemplates relocating downstream farms to a new secondary canal branching off from the original canal—thus effectively redesigning the tail area of the canal. In case these farms continue to experience poor harvests along the new secondary canal for at least five years, the system further considers relocating them to a new primary canal along the river (as illustrated in Fig. 3). Thus, there can be up to two movements to address poor harvest situations: when the first internal move does not result in higher yields, farms decide to start a new system themselves elsewhere. Movement is a response to water scarcity on farms.

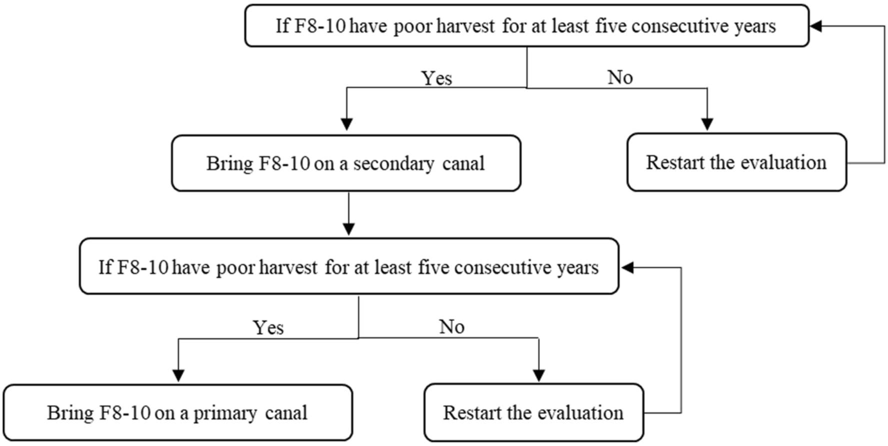

Fig. 3 The movement design logic of farms. Note: F—farm

System Expansion Decision-Making Processes

The expansion of the model irrigated system is triggered when farms achieve good yields for a consecutive period. If a good harvest situation—determined as upstream farms having five successfully harvested farmlands, while midstream and downstream farms have at least three harvested farmlands each—persists for a minimum of five years, the model considers expanding irrigation activities by introducing additional canals and farms. In total, there are eight expansion stages in sequence (Fig. 4). The maximum development of our model entails a total of 22 farms (from the initial amount of 10) along two primary canals and one secondary canal (from one original primary canal). Our model does not define where these new farms come from and how many farmers work in each farm—these new farmers could be migrants or family members of current farmers.

Farmland Reduction and/or Abandonment

Our study did not explicitly include the option for model farms to be abandoned—largely because our major interest in this paper is to discuss how to study under which conditions the (observed) expansion of irrigation in ancient Southern Mesopotamia may have occurred. Our modelling of the internal dynamics of farmlands did allow farms to return to and/or stay with the fallow status of fields within each respective farm, with this option depending on water resource availability. In situations with insufficient water resources within the system, downstream farms would confront the risk of having water shortages, which can potentially lead to diminished barley yields or, in severe cases, crop failure. As a proactive measure to mitigate these adverse consequences, farms may reduce the number of cultivated farmlands, essentially allowing some fields to revert to fallow status. It is important to underscore that this practice does not constitute farm abandonment as such but would have a similar effect on how the water resources are used. As we suggest in the outlook

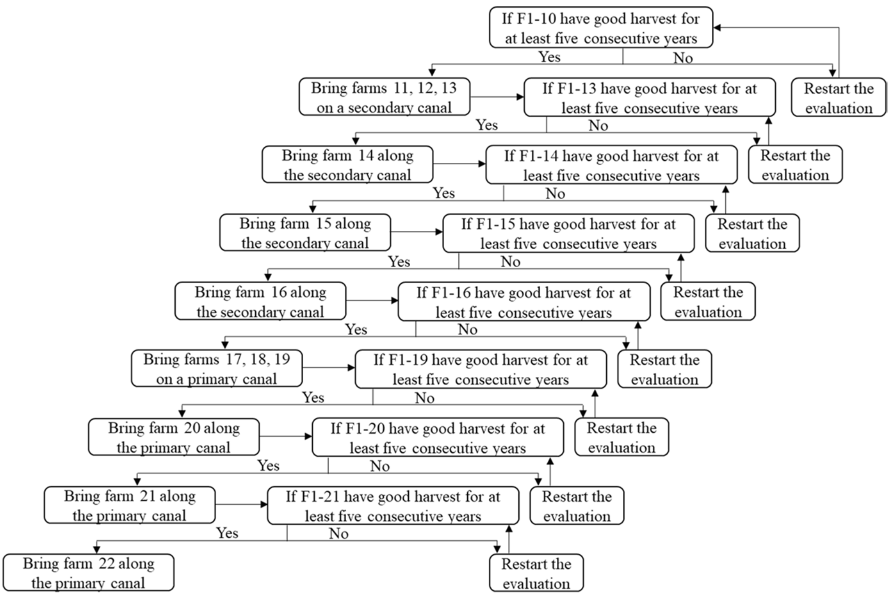

Fig. 4 The expansion design logic of canals and farms

at the end, it is indeed abandonment of farms that would fit in scenarios that require further study—as those cultivators that abandoned their fields may have become the producers of other important societal objects and services (like pottery, as may have occurred in the Hohokam area in modern Arizona (Zhu *et al.*, 2018)).

Gate Capacity Adjustment

According to Lang and Ertsen (2022a), farms are categorized as upstream, midstream, and downstream based on their respective locations along the same canal. In this research, the expansion scenario permits the inclusion of one secondary canal and one new primary canal. Consequently, the classification of upstream, midstream, and downstream farms determined by their positions along the same canal can change depending on the changes of the system size and farm locations. Since the expansion occurs gradually and the number of farms along a given canal increases over time, the composition of upstream, midstream, and downstream farms will vary as well. Table 1 provides a detailed description of the farms within these three groups.

Barley yields of farmers at farm level are evaluated every model year at the end of the growing season for farms located along the same canal. The harvest situation is determined based on this evaluation. Initially, all farms have the same initial gate capacity (IGC) for their irrigation needs. In the event of a poor harvest situation, collective decision-making comes into play for adjusting the gate capacity (GC) of upstream and midstream farms, while downstream farms maintain the original IGC. The adjustment of GC can occur continuously over multiple years, as it is driven

Table 1 The list of upstream, midstream, and downstream farms

Canals	Expansion times	Farms	Upstream farms	Midstream farms	Downstream farms
Primary canal 1	Initial	F1–10	F1–3	F4–7	F8–10
Secondary canal	The first expansion (from F10 to F13)	F11–13	F11	F12	F13
	The second expansion (from F13 to F14)	F11–14	F11	F12–13	F14
	The third expansion (from F14 to F15)	F11–15	F11	F12–14	F15
	The fourth expansion (from F15 to F16)	F11–16	F11–12	F13–14	F15–16
Primary canal 2	The fifth expansion (from F16 to F19)	F17–19	F17	F18	F19
	The sixth expansion (from F19 to F20)	F17–20	F17	F18–19	F20
	The seventh expansion (from F20 to F21)	F17–21	F17	F18–20	F22
	The eighth expansion (from F21 to F22)	F17–22	F17–18	F19–20	F21–22

by potentially persistent lower yields experienced by downstream farms, rather than being a one-time adjustment. The equations of GC adjustment were calculated as

$$UGC = IGC - (CPHY + 1) * 10 \tag{1}$$

$$MGC = IGC - CPHY * 10 \tag{2}$$

where UGC means the gate capacity of upstream farms; CPHY means the continuous lower yields years for downstream farms; MGC means the gate capacity of midstream farms. The lowest value of UGC and MGC is 30 WU/tick (WU: water units, which are used to represent water volumes), which is also the lowest boundary of GC in this research.

Scenarios

Considering the combinations of (1) varied river discharge (RD) and gate capacity (GC), (2) the adjustment year of GC, (3) the continuity of good or poor harvests, and (4) the memory of harvest barley and water availability, the current model encompasses a total of 2880 possible scenarios (Table 2). The GC adjustment or variation (GCV) indicates whether the gate capacity is adjusted annually or every two years. The memory (M) of harvesting barley and available water is based on the past 10 years or 20 years, which influences the actual decision-making process. These variations in scenarios allow for a comprehensive exploration of the dynamics within the model, providing a wide range of possibilities for analysing the interactions and outcomes of the model irrigation system. The sheer amount of results also forces us to select a few specific scenarios to discuss the results of IRABM[3] (see below).

Gini Coefficient and Lorenz Curve

The distribution of barley yields among farms in response to model system dynamics was analysed using the Lorenz curve and Gini coefficient—with the Gini coefficient derived from the Lorenz curve (Lorenz, 1905). To construct the Lorenz curve, we plotted the cumulative fraction of total yields (y) from lowest to highest against the cumulative fraction of the number of farms (x) from lowest to highest. This curve provides a visual representation of the distribution of yields among farms. The Gini index is calculated as the ratio of the area between the perfect equality line and the Lorenz curve (A) divided by the total area under the perfect equality line (A + B) (Fig. 5). Per definition, the Gini coefficient ranges from 0 to 1, with a coefficient closer to zero indicating a more equal distribution of yields among farms. Often, a Gini coefficient value of 0.4 is considered a "warning line" for income (or yields in our research) distribution gaps, indicating a significant level of inequality in the distribution of wealth among users (Sitthiyot & Holasut, 2020). The calculation equation of the Gini coefficient is as follows (Harch *et al.*, 1997; Sadras & Bongiovanni, 2004):

Table 2 The overview of the parameters and scenarios

Parameters	Value	Increment	Units	Scenarios
Simulation years	100	\	year	\
RD	50–600	50	WU/tick	20
GC	30–200	10	WU/tick	18
GC adjustment variation	1–2	1	year	2
Continuously poor harvest years	5	\	year	1
Continuously good harvest years	5	\	year	1
Harvest memory	10–20	10	year	2
Available water memory	10–20	10	year	2
Total	\	\	\	2880

1. Gate capacity adjustments are commonly influenced by factors such as crop rotation, crop varieties, water availability, climate variability, changes in irrigation system, soil conditions, and environmental regulations (Zhang *et al.*, 2021). However, it is important to note that these factors exhibit a relatively stable pattern and/or are not within the scope of consideration in our current research, specifically within our study area. Moreover, our research exclusively focuses on the cultivation of barley, and our decisions regarding GCV are predicated on the comparison of yields among farms. As a result, we have chosen to implement an annual basis for GCV adjustments in our study. Initially, we conducted model runs using GCV values of 1, 2, 3, 4, and 5 years. However, when analysing the outcomes for GCV values of 3, 4, and 5 years, it became evident that these adjustments offer minimal benefit to farms experiencing poor harvests—their yields remain largely unaffected, or any improvements are marginal at best. Notably, a trend emerges where higher GCV values correspond to diminishing assistance. Consequently, we have opted to exclusively present GCV values of 1 and 2 years in this paper. 2. We have opted for the M of 10 years and 20 years for our analysis based on the following considerations: (1) Farming decisions are often informed by past experiences, such as weather patterns, soil conditions, crop performance, pest and disease occurrences, and other elements influencing agricultural outcomes; (2) While some farmers possess traditional knowledge handed down through generations, offering insights spanning decades or even centuries, others might have a more limited historical perspective due to being newer to farming practices; (3) It is important to acknowledge that rapid shifts in agricultural systems can constrain the depth of historical experience, owing to changes in methodologies and technologies; (4) Notably, there is a lack of detailed historical records pertaining to agricultural practices in Southern Mesopotamia, further affecting the scope of available evidence; (5) We aimed to provide a substantial historical perspective which allows to capture long-term trends and patterns in factors such as climate, crop, and water. It is important to note that the choice of a 10 and 20-year period for farmers' memory years is context-dependent. The specific length of the memory period is determined by the research objectives, the nature of the agricultural system under study, and the availability of reliable historical data. We aim to strike a balance between capturing meaningful trends and maintaining practical relevance for farmers' decision-making

$$G = 1 - \int_0^1 L d_x \tag{3}$$

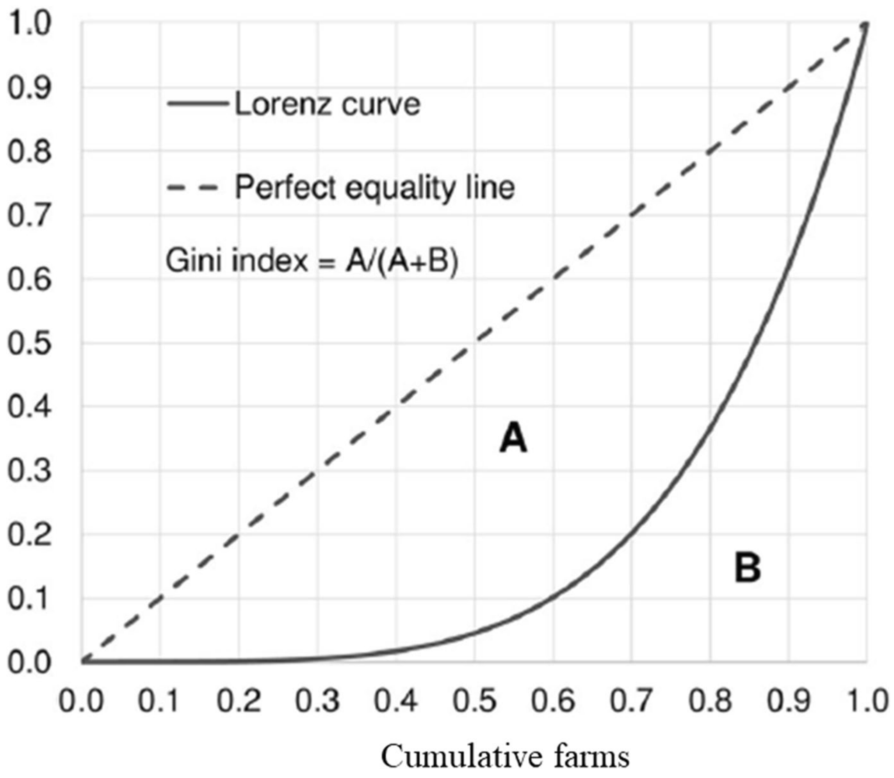

Fig. 5 Lorenz curve

Results

Dynamics of the Irrigation System in a 100-Year Simulation

The Movement Patterns of Farms and Canals

The Movement Year of F8–10 As mentioned, the design of IRABM[3] allows for a maximum of two movements in case yields are low, depending on water availability. The first movement involves relocating F8–10 from the initial primary canal to a newly established secondary canal when their yields along the original primary canal proves to be inadequate. Regrettably, should F8–10 continue to experience poor harvest even after transitioning to the new secondary canal, the second movement will be initiated. This involves relocating F8–10 from the secondary canal to a new primary canal 2 (Fig. 6). Depending on water and time controls, the movement time of F8–10 varied considerably in the different scenarios (Table 3).

- For RD = 50 WU/tick, the two movements are always completed by the model (agents). For each movement, the movement year varies with increasing GC: the

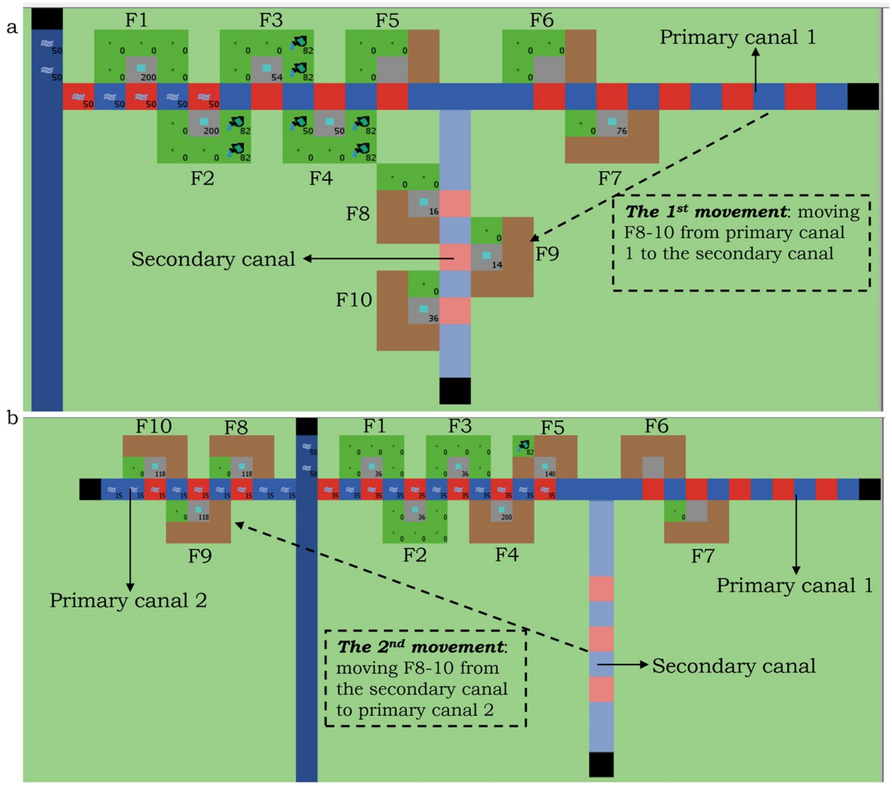

Fig. 6 The layout of irrigation system regarding the two movements. Note: The figure illustrates two sequential movements: a, The 1st movement occurs when unfavourable harvest situations persist for at least 5 years among farmers situated upstream, midstream, and downstream along the initial primary canal. At this point, the system contemplates initiating a secondary canal and relocating downstream farmers (F8–10) to this secondary canal in order to assist them in enhancing their crop yields. b, In the 2nd movement, if F8–10 still experience poor harvests at the new location in comparison to F1–7 who stay along the initial primary canal, the system will consider establishing a new primary canal. This would involve transferring F8–10 from the secondary canal to the new primary canal, thereby aiding them in improving their yields

year increases first before decreasing to a value, that is kept until the highest simulated GC. Harvest memory and available water memory create differences in the movement year, with the combination lower GC – higher M creating an earlier movement year.

- For RD = 100 WU/tick, the first movement occurs only when the GC is higher—indicating that in many cases the yields are not too bad. When GCV is set to 1 year, the movement occurs when the GC exceeds 140 WU/tick. When GCV is set to 2 years, the movement takes place when the GC is above 110 WU/tick. Moreover, the movement year increases as the GC increases for M = 10 years, whereas the movement year remains constant regardless the GC

Table 3 The movement year of F8–10 when there is poor harvest situation

RD (WU/tick) / Movement Year / GC (WU/tick)	M = 10 years, GCV = 1 year				M = 10 years, GCV= 2 years				M = 20 years, GCV= 1 year				M = 20 years, GCV = 2 years			
	50		100		50		100		50		100		50		100	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
30	18	28	16 E	\	18	28	16 E	\	33	43	16 E	\	33	43	16 E	\
40	39	49	17 E	\	39	49	17 E	\	33	43	17 E	\	33	43	17 E	\
50	39	49	17 E	\	39	49	\	\	33	43	17 E	\	33	43	\	\
60	39	49	\	\	39	49	\	\	20	30	\	\	20	30	\	\
70	17	27	\	\	13	23	\	\	20	30	\	\	13	23	\	\
80-110	14	24	\	\	14	24	\	\	20	30	\	\	14	24	\	\
120	14	24	\	\	14	24	10	\	14	24	\	\	14	24	10	35 E
130	14	24	\	\	14	24	11	\	14	24	\	\	14	24	10	36 E
140	14	24	\	\	14	24	12	\	14	24	\	\	14	24	10	38 E
150	14	24	10	\	14	24	13	\	14	24	10	30 E	14	24	10	40 E
160	14	24	11	\	14	24	14	\	14	24	10	32 E	14	24	10	43 E
170	14	24	12	\	14	24	15	\	14	24	10	32 E	14	24	10	44 E
180	14	24	13	\	14	24	16	\	14	24	10	33 E	14	24	10	47 E
190	14	24	14	\	14	24	17	\	14	24	10	33 E	14	24	10	49 E
200	14	24	15	\	14	24	18	\	14	24	10	35 E	14	24	10	50 E

E—expansion of the farms and canals after the movement

levels when M = 20 years. The table also suggests that expansion occurs for RD = 100 WU/tick when GC < 60 WU/tick or GC > 110 WU/tick.

- An intriguing discovery for M = 20 years is that in several situations farms first relocate due to poor harvest situations, after which the system expands as a result of the substantial profits generated by F8–10 (in the table indicated with "E"). This indicates the success of the F8–10 movement, as it did not only benefit farms but also benefits the entire system leading to an increase in total yields and attracting more farms to join the system. We discuss expansion because of good harvests further below.

In summary, for RD = 50 WU/tick, the variation of M and GCV has little influence on the movement year. For RD = 100 WU/tick, the variation of memory influences the movement situations—farms tend to move earlier with a longer memory, with subsequent expansions along the secondary canal after the initial movement.

The Influence of Movement to Farms The influence of movement on all modelled farms is shown in Fig. 7. The figure may be a little complex, but

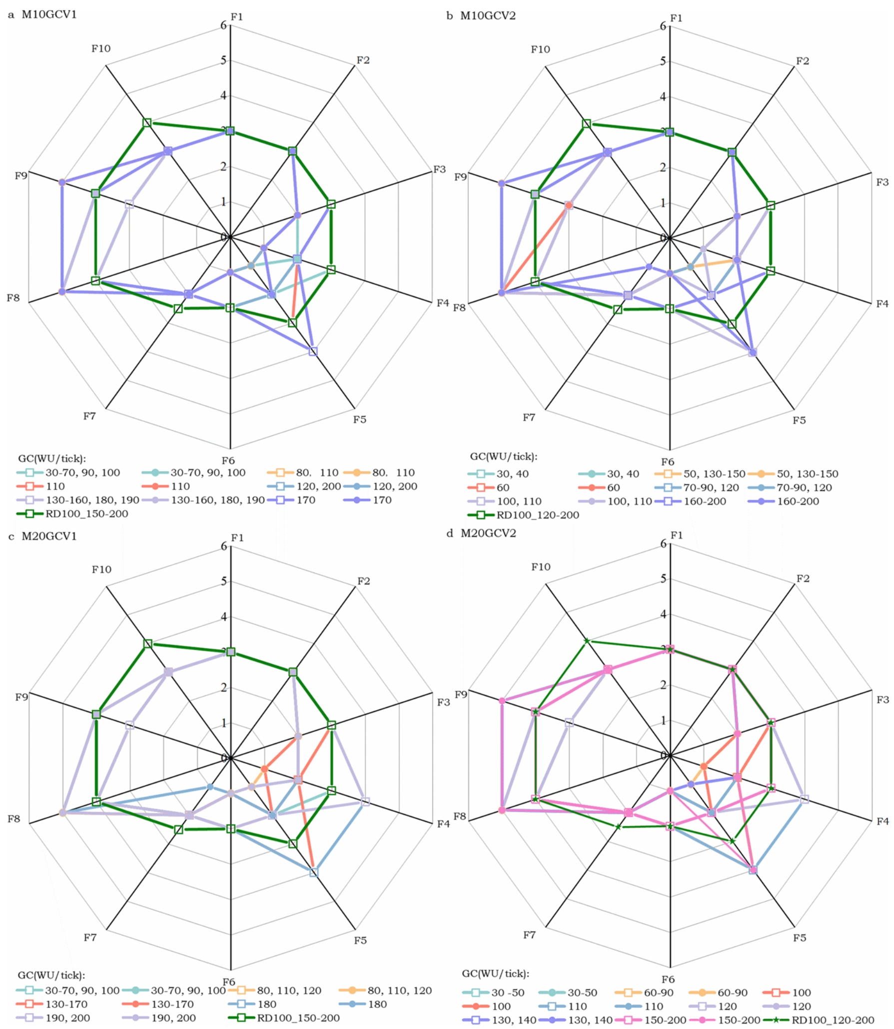

Fig. 7 The influence of movement to farms. Note: We use numbers 1–5 to present the yields change of farms after the two movements: where 5—further increase (yields increased again after the second movement); 4—increase (yields increased after the first movement); 3—keep (yields remained the same after two movements); 2.5—decrease after the first movement and then increase after the second movement; 2—decrease (yields decreased after the first movement); 1—further decrease (yields decreased again after the second movement). M10, M20—memory of 10, 20 years; GCV1, GCV2—adjust GC every year, every two years. Line + square shows the influence of the first movement while line + dot shows the influence of the second movement. For RD = 100 WU/tick, there is only one movement shown with deep green. All of the other colors show the situation of RD = 50 WU/tick and are sorted with different GC groups

demonstrates that the movements have a more intricate impact on farms for RD = 50 WU/tick compared to when RD = 100 WU/tick. To start with the higher RD, for this RD = 100 WU/tick, the movement had no impact on

F1–5. In contrast, F6 experienced lower yields, and F7 initially had lower yields for the first few years but then returned to initial levels. However, the movement proved beneficial for F8–10, as they could increase yields. For RD = 50 WU/tick, the impact on the farms that did not move (F1–7) exhibits many more variations:

- F1 and F2 consistently maintain their barley yields, unaffected by the movements.
- The first movement has no effect on F3, but the second movement reduces yields for this farm.
- Starting from F4, the impacts of movements on farms become more complicated. For certain GCs, F4 manages to maintain yields after the first movement but experiences a decrease after the second movement—especially in scenarios with M = 20 years. For other GCs, F4 consistently experiences a decline in yields.
- Starting from F5, farms are no longer able to retain their initial yields after the first movement of more downstream farms. For GCV = 1 year, there are two situations regarding the impact on F5: either yields decrease twice or they increase after the first movement but decrease after the second movement. For GCV = 2 years, in one situation F5's yields decrease after the first movement and increase after the second.
- Yields of F6 and F7 decreased twice due to the movements under all scenarios. F6 always had no yields after the second movement, while for F7, the first movement reduces its yields to zero.

According to Fig. 7, the movements influenced F8–10 (the farms that actually moved) differently as well. F8 benefitted the most from the decision to move, as its yields increased after both movements. The movements also helped F9 achieve higher yields—either maintaining initial yields and then increasing or increasing twice. However, the two movements did not lead to an increase in yields for F10. While F10 experienced an increase in yields in the first few years, the successful movement and expansion of F8 and F9 resulted in these two farms acquiring more water for their own farmland expansion. Consequently, after a promising start, F10 continued to experience what the most downstream farms in a gravity system may face: less water for irrigation and eventually having no yields.

The Influence of Movement on the Irrigation System Figure 8 illustrates the comparison of total system yields before and after the movements for RD = 50 and 100 WU/tick. In the case of RD = 100 WU/tick, it is evident that total system yields increase following the movement—with a generally decreasing trend in total yields as GC increases. In contrast, for RD = 50 WU/tick, the situation is more diverse. Under certain GCs with GCV = 1 year, there is a decrease in total yields after the first movement. Furthermore, when GCV = 2 years, total system yields are lower after the first movement when GC exceeds 130 WU/tick. However, regardless of the scenarios, total system yields increase after the second movement. The movements had less influence on the head farms, but affected tail farms. Initially, movements were able

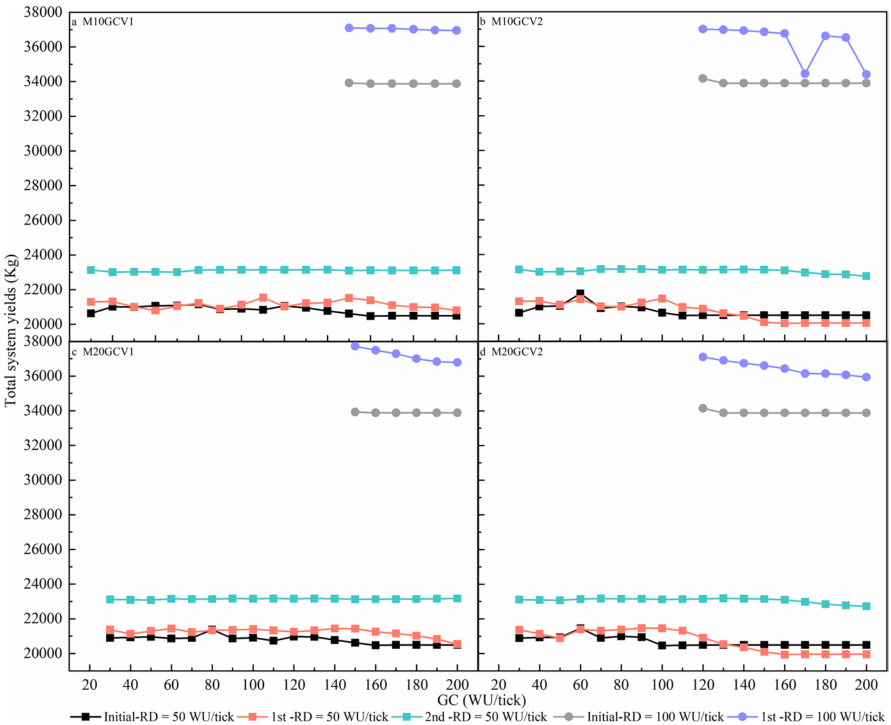

Fig. 8 The influence of movement to the total system (10 farms)

to address poor harvest situations, but once the farms relocated and settled in new areas, the issue of how to share the common pool water resource (Ostrom & Gardner, 1993) arose once again. As a result, the improvement in yields for farms did not align consistently with the improvement of the overall system. These sensitivity analyses indicate that factors such as the location of farms along the same canal, GC, RD, and the time of movements have a significant impact on farms' yields. On the other hand, the memory years and GC variation years have a relatively minor influence on farms' yields.

The Expansion of Farms and Canals

The eight consecutive expansion decisions implemented in this model (Fig. 4) contribute to the gradual growth of the irrigation system. For the largest model area that we can reach in IRABM[3], F1–10 are situated along the original primary canal 1, F11–16 are along the new secondary canal, and F17–22 are along the new primary canal 2 (see Fig. 9). Each expansion resulted in an overall increase in total system yields, although the impact on farms varied.

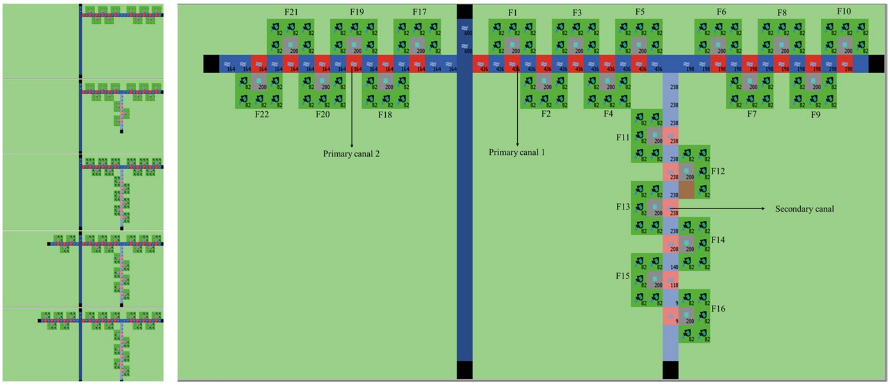

Fig. 9 The sequence of expansion (left) and the fully expanded irrigation system (right)

The Expansion Year of New Farms (F11–F22) Overall, our model results indicate that combinations of RD and GC have the potential to trigger expansions in any given year, but that actual expansions of new farms exhibit notable variation depending on the combinations of RD and GC. To simplify the visualization and explanation in this section, we categorized expansion years in five levels. In this text, we will introduce the farms' expansion year patterns with M = 10 years and GCV = 1 year in detail (Fig. 10). Details for the other three M and GCV combinations can be found in Figs. 14, 15, and 16 in Appendix 2.

When RD = 150 and 200 WU/tick (the lowest two rows in Fig. 10), the system could not fully expand:

- For RD = 150 WU/tick, only F11–13 expanded, finishing in Expansion Year Level 1 (EYL1—for definitions of this and other terms used in this overview see Fig. 10).
- For RD = 200 WU/tick, the system could be expanded to F21: F11–13 expanded in EYL1 under all GCs scenarios; F14–21 expanded under some GCs scenarios—F14 and F15 expanded in EYL2, EYL3, and EYL5, F16 expanded in EYL3, EYL4, and EYL5, F17–19 expanded in EYL3 and EYL5, while F20 and F21 only expanded in EYL5.

When RD > = 250 WU/tick, the system could fully expand, but not for all GCs:

- EYL1: F11–13 could expand in this level under all combinations of RDs and GCs, while F14 could also expand in this level except for when GC = 30 and 50 WU/tick..
- EYL2: when RD = 250 WU/tick, F15 expanded with most GCs, while F16 finished expansion with three GCs; when RD > 250 WU/tick, F15–19 could finish the expansions except for some combinations of GC > 110 WU/tick and RD = 300–450 WU/tick.

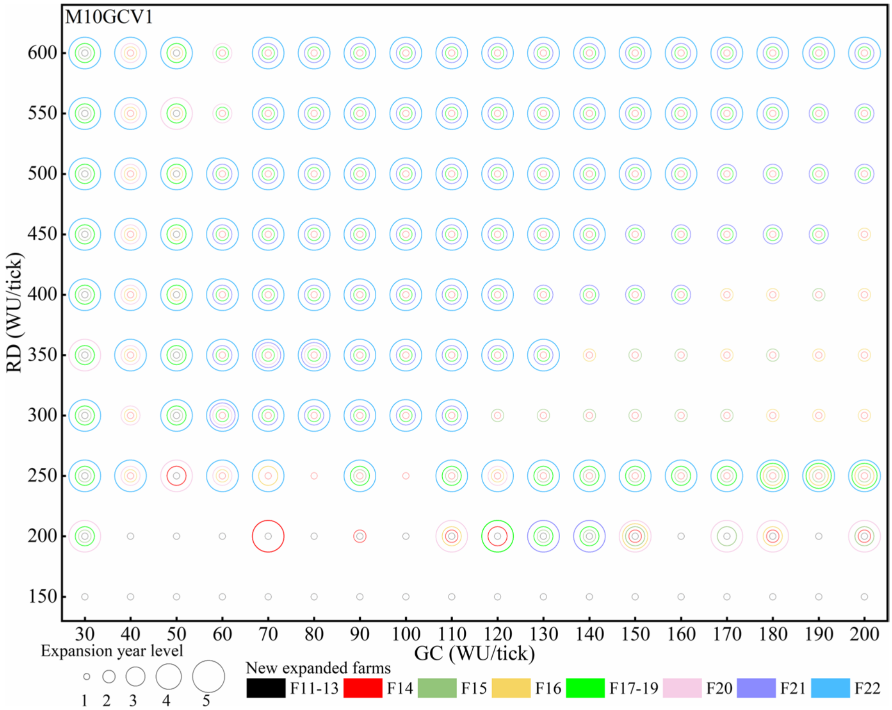

Fig. 10 The expansion year of new farms when there is good harvest situation. Note: for Expansion Year Level: 1—expansion in year 10–27; 2—expansion in year 28–45; 3—expansion in year 46–63; 4—expansion in year 64–81; 5—expansion in year 82–100. There is no relation between the size of expansion year level and the id of the new farms. The farms could be expanded in any year, for instance, when GC = 70 WU/tick, F14 expanded in level 5 with RD = 200 WU/tick while F14 expanded in level 1 with RD = 250 WU/tick. The combinations of RD and GC could bring all possible expansion years for all new farms

- EYL3: when RD = 250 WU/tick, F16–19 expanded with most GCs; when RD > 250 WU/tick, F20–21 could finish the expansions except for some combinations of GC > 110 WU/tick and RD = 300–450 WU/tick.
- EYL4: only 7 scenarios show that farms expanded in this level: F16 (RD = 200 WU/tick and GC = 150 WU/tick); F17–19 (RD = 250 WU/tick and GC = 180–200 WU/tick), F21 (RD = 300 WU/tick and GC = 60 WU/tick), and F21 (RD = 350 WU/tick and GC = 70–80 WU/tick).
- EYL5: F20–22 expanded in this level when RD = 250 WU/tick with most GCs; when RD > 300 WU/tick, F20–21 expanded in this level with GC = 30–50 WU/tick, while both of higher RD and GC show more F22 expanded situations in this level.

For different M and different GCV, there were no clear differences observed in terms of the expansion year or the number of farms involved in the expansion. A more or less consistent pattern can be detected from the figures (Figs. 10, 14–16):

- Across all RDs, the expansion of F11–13 was completed before the 28th model year, categorizing it as EYL1. However, only one expansion took place when RD was set to 150 WU/tick.
- More expansions commenced when RD increased to 200 WU/tick, although the first fully expanded irrigation system was only achieved when RD reached 250 WU/tick.
- With more farms or more farmlands in the system, the expansion years occur later.
- To be fully expanded, both RD and GC played vital roles. The combinations of higher RDs and low to upper-medium-range GCs had a higher likelihood of achieving full expansion. These combinations actually resulted in a more equitable distribution of water in the irrigation system as well (which may also be an important factor for successful societal development, see further below).

The Influence of Expansion to Farms Due to the complexity of the different aspects of farms expansion and the effects, it is difficult to present the results through figures. Therefore, in this section, we provide a simplified explanation of the findings. Throughout the expansion process, F1–6 consistently achieved the highest yields, regardless of the progression of the expansion. When analysing the original dataset of farm yields after the expansions, it was observed that expansions had an impact on the yields of F7–20. As the expansions were implemented gradually, the farms who expanded earlier were inevitably impacted by those who expanded later. Among the impacted ones, F9–12 were most affected by expansions. However, it is important to note that the yields of the affected farms did not drop to zero. There was still some yield despite the (influence of the) expansions. This general observation brings us to the (in)equalities in annual barley yields within the model farms' communities.

Barley Yields Inequality

In total, we have 18 GCs to analyse for potential unequal yields with a series of RDs. As values in the ranges of GC = 30–50 WU/tick, 60–140 WU/tick, and 150–200 WU/tick show similar patterns for each range, we focus on three specific cases: (GC = 30, 120, and 200 WU/tick) to clearly illustrate the Gini variations (Figs. 11, 12, and 13). As demonstrated earlier, the dynamics of the irrigation system were minimally affected by M and GCV. Therefore, for these GCs, the Gini variation is presented for different RDs for the combination of M = 10 years and GCV = 1 year. For information regarding the Gini values for other GCs, please see Appendix 3 (Fig. 17).

The fluctuations of Gini values over time are readily observable in each figure. Fluctuations align with the expansion periods of farms and canals. Gini values tend to be higher in the years directly following an expansion or movement and gradually decrease over time afterwards. This indicates an initial increase in inequality of yields during the early stages of expansion or movement, which subsequently decreases until the next expansion or movement occurs. The new farms initially

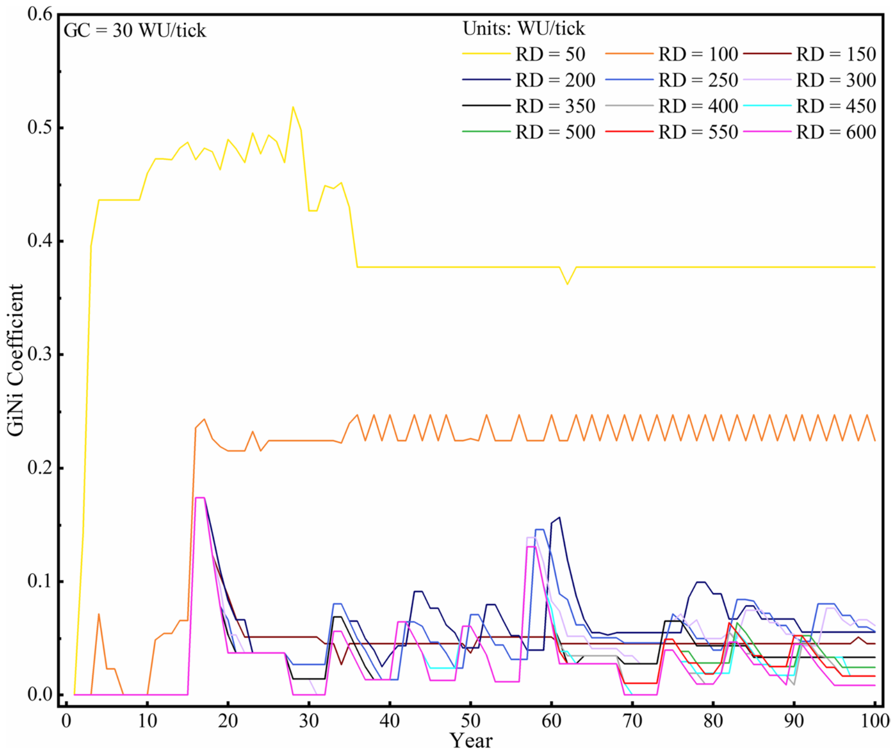

Fig. 11 Barley yields Gini coefficient through 100 years (GC = 30 WU/tick)

cultivated one field on their model farmland and then expanded their farmlands based on their experienced successes. Consequently, the yields of farms exhibited significant variation in the early years, but gradually became more similar over time. This trend may illustrate the potential tension in irrigated landscapes, when individuals decide to change something to improve their position, with potential negative effects on the short term for equal distribution of benefits. It is not automatically given that the farms whose actions are affected will accept such a change, even when on the longer term the larger group might benefit. This example illustrates the importance of taking short-term interactions into account: what might become beneficial on the longer term may not become reality because of inequalities and consequent struggles on the short term.

The highest Gini values are observed for the lowest RD (50 WU/tick). These values often exceed 0.4, which surpasses the warning threshold for inequality. This assertion is further supported by Basri and Lawrence (2020), who highlighted the relationship between house size inequality and urbanism. Their research indicates that Gini values for rural agricultural settlements below 5 hectare consistently remain below a Gini value of 0.4. For RD exceeding 50 WU/tick, the Gini values remain below 0.4, indicating a more equitable (but not equal) distribution of annual yields. For each higher RD, Gini values gradually have fewer fluctuations over time

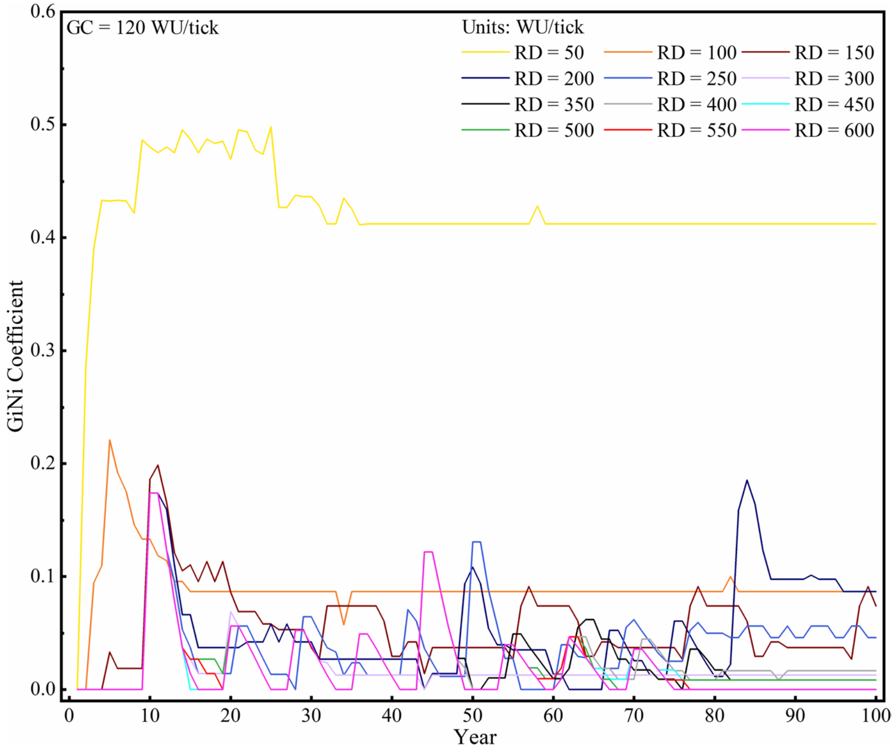

Fig. 12 Barley yields Gini coefficient through 100 years (GC = 120 WU/tick)

and stay at lower values. For RD = 600 WU/tick, which is also the highest simulated RD in our research, Gini values are consistently low with only slight fluctuations. These observations support the obvious observation that expansion is easier when sufficient water is available, as a more equal distribution of yields among farms reduces competition for resources. It also creates a potential opportunity to share the surplus with new members of the system. Sufficient resources facilitate a more equitable distribution of resources. However, when systems expand even further—beyond our modelled maximum area—it is to be expected that relative scarcity of water will put pressure on the equal sharing of wealth—possibly leading to some actors shifting activities, like trade or crafts, as for example discussed in Zhu *et al.* (2018) for the Hohokam irrigated areas (located in modern Arizona).

Discussion

Decision-Making Mechanisms in IRABM^3

The findings of this study highlight the capabilities of IRABM^3 in capturing the complexities of decision-making in irrigation system use and management. The

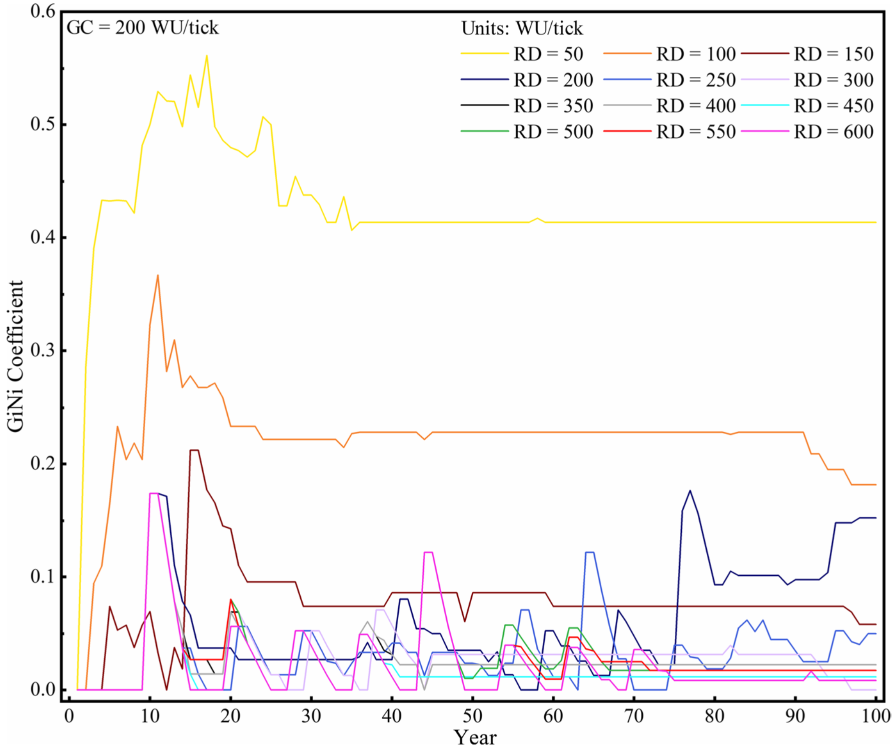

Fig. 13 Barley yields Gini coefficient through 100 years (GC = 200 WU/tick)

results emphasize that key factors influencing barley yields in response to farms' decisions include RD, GC, farms' location, and the independent or collective outcomes arising from those decisions. These factors are closely connected to (distribution of) water availability, aligning with the inherent nature of irrigated agriculture and corroborating existing literature in the field (D'Odorico *et al.*, 2020; Gomez-Zavaglia *et al.*, 2020; Rosa *et al.*, 2019). These factors contribute to the complexity of irrigation systems, including the dynamics of farmlands and the expansion or movement of canals and farms. This indicates that the current model effectively captures decision-making mechanisms operating at different levels, as per the objectives of the agents involved. Decision-making is a multifaceted process that involves both independent and collective dimensions. Commonly, initial decisions made at lower levels have the potential to develop into decisions at higher levels. These collective decisions can have varying degrees of impact on the agents involved, shaping the dynamics of the system (Ertsen *et al.*, 2014; Holman *et al.*, 2019; Wens *et al.*, 2019). Please note again that we did not specifically assume who would make these decisions: we did include decisions related to different locations in the model system.

Generally, one could expect stakeholders in irrigation systems to be willing to share limited water resources (D'Exelle *et al.*, 2012; Geertz, 1972; Li *et al.*, 2019; Tilmant *et al.*, 2009). However, when farm(er)s make decisions, they often prioritize their own goals without considering to directly the demands of others. These actions exacerbate the issue of "common pool resource management" (Albiac *et al.*, 2020; Ostrom & Gardner, 1993). Through more collective (or coordinated) decision-making processes, such as adjusting the GC for water re-allocation in our model, it is possible to partially improve the yields of farms experiencing poor harvests. We propose that incorporating direct social interactions among farms in the modelling, such as neighbourhood effects, can create further options to study effects of addressing unequal water distribution by model agents (Bell *et al.*, 2016; Rasch *et al.*, 2016).

From a broader perspective of irrigation systems (Ertsen *et al.*, 2014; Merot *et al.*, 2008; Robertson & Wang, 2004), we argue that the intricate relationship between irrigation activities and water availability, the heterogeneity with collective system and farms characteristics, the relevance of short and long-term decisions, and the uncertainty associated with crop production are important properties of decision-making. Understanding and accounting for these properties is crucial in comprehending and analysing decision-making dynamics in the context of irrigation systems. The framework proposed in this research for structuring irrigation-related ABM is the third version of the two existing frameworks (Lang & Ertsen, 2022a, 2022b). Additionally, it incorporates elements of the Overview, Design concepts, and Details + Decision-making (ODD + D) protocols to comprehensively describe decision-making processes within ABMs. This framework provides a holistic approach to understanding irrigation systems by considering both farms and collective irrigation system perspectives, thus enhancing the overall descriptive capacity of the IRABM^3 model.

The Dynamics of Farmlands, Farms, and Canals

The IRABM^3 effectively captures the processes of expansion/reduction of farmlands and the expansion/movement of canals/farms. Furthermore, the model extensively explores the dynamic interactions arising from decision-making across different levels. In gravity-based irrigation systems, it is observed that upstream farms tend to achieve higher yields and can consider expanding their farmlands, whereas downstream farms experience lower or no yields and may contemplate reducing (part of) the farmlands. These findings highlight the presence of "common pool resource" issues, wherein conflicts arise due to the sharing of limited water resources when the irrigation management decisions of upper farms impact the agricultural productivity of lower farms (Becu *et al.*, 2003).

It is important to note that achieving one's personal goals in this context may come at the expense of sacrificing the profits of others (Murphy *et al.*, 2019). However, in cases where collective action, such as water redistribution, is implemented in the system, farms have the opportunity to keep maximizing yields within a farm while also assisting farms—with lower yields—apparently sharing water does not automatically reduce yields of upstream users. Our results show the complexity of yields pattern and farmlands pattern—the (partial) improvement of poor harvest situations with (1) the increase of total system yields; (2) the sacrifice of upper farms and an increase of total system yields; (3) the sacrifice of upper farms and a decrease of total system yields; and (4) the expansion or reduction of farmlands, which aligns with the corresponding changes in yields.

The expansion and movement patterns of farms and canals in our model environment can be simplified as follows: if the annual decision-making regarding farmland dynamics and GC adjustment leads to a mutually beneficial outcome for farms and the irrigation system, and this situation persists over time, the model system will prioritize the inclusion of more farms, construction of new canals, and gradual development towards a more fully established irrigation landscape. Conversely, if the annual decision-making fails to improve the poor harvest situation, the model system will consider relocating the affected farms to a different canal. These patterns reflect the ongoing efforts to optimize the irrigation system based on the outcomes of continuous decision-making processes—in our model based on annual results. These phenomena support the theory that short-term, farm-level decision-making has the potential to drive long-term, community-level development (Ertsen, 2016; Ertsen *et al*., 2014). The decisions made by farms in the short term, such as optimizing their own yields and addressing immediate challenges, can collectively contribute to the overall progress and development of the irrigation system over time. This highlights the interconnectedness between actions at farm level and the broader community outcomes, emphasizing the importance of considering both short-term and long-term perspectives in decision-making processes. Please note that both (or a combination of) expansion of successful system and movement of unsuccessful farms to new systems may have created an expanded irrigated area as it would have developed in ancient Southern Mesopotamia. It is likely that distribution of benefits would have been a key factor in Mesopotamia's history.

Yields Inequality in the Developing Irrigation System

Actually, many archaeologists have put forward the notion that water availability was never a limiting factor impeding the growth of the irrigation system in Southern Mesopotamia as water regimes of Tigris and Euphrates could support the diachronic development of irrigation management from dispersed, small-scale to large-scale, and finally to empires-scale (Adams, 1981; Rost, 2017; Wilkinson & Jotheri, 2016; Wilkinson *et al*., 2015). The application of the Gini coefficient to barley yields has allowed us to analyse the distribution of yields among farms and examine the degree of inequality within the system. These findings not only support current narratives and knowledge about the region but also shed light on additional aspects that can be explored in future studies. Our analysis of Gini values reveals that the distribution of barley yields within the growing irrigation system was relatively equal. This implies that while river discharge is a significant factor influencing the harvest situation and decision-making, the same water supply does not seem to create unequal development of/within the irrigated areas.

One intriguing finding from the analysis of the Gini coefficient is the correlation between its fluctuation and the dynamics of the irrigation system. The Gini values consistently exhibited a pattern of increasing to a peak value in the first year of expansion/movement, followed by a gradual decrease to a certain level that was maintained for several years. Subsequently, the values exhibited a cycle of periodic increase and decrease until the end of the simulation period. Remarkably, this patterns of Gini values increasing at the initial stage after expansion aligns with archaeological evidence that highlights the occurrence of increasing inequality during the early stages of urbanization or the transition from small-scale to large-scale communities, with the formulations of new social, economic, and political arrangements (Baker, 2022; Basri & Lawrence, 2020). However, our study exclusively concentrates on the expansion of farmlands and canals, as opposed to delving into the unconstrained expansion of farmlands. Taking this perspective, it becomes conceivable that larger farmland sizes could lead to higher Gini values. This conjecture totally aligns with earlier research that has demonstrated a consistent rise in Gini values corresponding to larger house sizes (Basri & Lawrence, 2020; Squitieri & Altaweel, 2022). If we can include measuring Gini values with the agricultural land size, our research would furnish and endorse a viewpoint concerning the urbanization of societal development.

Modelling Advantages and Challenges

Our IRABM^3 framework offers several notable advantages. One key advantage lies in its ability to integrate essential concepts such as the willingness to on individual (farm) and collective (system) levels (Mezgebo *et al.*, 2022), decision-making (Elsawah *et al.*, 2015), and different agent types (Kaiser *et al.*, 2020). By combining these elements, the framework provides a comprehensive approach that captures the complexity and interplay of factors involved in the decision-making processes within an irrigated-agricultural context. According to our model design, the irrigation decision-making takes place on three time scales: (1) decision-making process for farmland dynamics occurs on an annual basis, (2) the GC adjustment is considered either annually or every two years, and (3) system expansion or movement is evaluated based on at least five years of harvest data. Meempatta *et al.* (2019) summarized the temporal scales of irrigator decision-making into three categories: tactical (decisions made within a short-term time frame of less than one year), strategic (decisions considering medium-term goals and objectives that span one to five years), and structural (decisions with a long-term perspective, extending beyond five years). Various studies have employed qualitative, quantitative, and mixed methods to model and analyse irrigators' decision-making processes on irrigation water management, farmlands management, and crop management (Arnall, 2014; Dury *et al.*, 2013; Gras, 2009; Marques *et al.*, 2006; Meempatta *et al.*, 2019; Mireille & Marianne, 2007; Niles *et al.*, 2015). Related to these studies, the IRABM^3 framework demonstrates its robustness and reliability in simulating irrigator decision-making in irrigation management. The flexibility and generality of the framework can be extensively applied to irrigated agricultural systems worldwide, allowing for the investigation of long-term perspectives, such as the evolution of the irrigation system in Southern Mesopotamia. Another advantage of the framework is the incorporation of sensitivity analysis, which allows for the identification of influential factors affecting yields and decision-making. This could help to enhance the model's performance and policy relevance (Ligmann-Zielinska *et al.*, 2014).

Obviously, we still face challenges in terms of data availability. Future research should aim to address these limitations and explore additional perspectives: (1) incorporating direct communication and interaction among farms into the model to provide a deeper understanding of different levels of patterns in irrigation systems that may have been previously overlooked; (2) acquiring additional relevant crop and water data for model validation to strengthen the model, and also contribute to the validation challenges of ABM in general (Filatova *et al.*, 2013; Heppenstall *et al.*, 2021).

We designed our virtual irrigation system with a maximum of 22 farms, two primary canals, and one secondary canal within a 100-year simulation. The outcomes of our model indicate the potential for further expansion of farmlands, an increase in the number of farms, and the construction of additional canals under conditions of higher water availability, enhanced communication among farms, or extended simulation time. This insight aligns with the historical development of irrigated landscapes in Southern Mesopotamia. Over time, these irrigated (hydraulic) landscapes underwent a transformation, progressing from areas along levees to areas natural or human-made canals, transitioning from small-scale to large-scale systems, eventually culminating in the establishment of systems under central management—including but not necessarily limited to the famous herringbone patterns (Altaweel, 2019; Rost, 2017; Wilkinson & Jotheri, 2016; Wilkinson *et al.*, 2015). The Gini coefficient, when applied to farms' production, appears a promising tool for characterizing the development of an agricultural-based society. It is conceivable that by factoring in diverse forms of collective engagement, such as community-level administration, state oversight, and imperial patronage in the management of irrigated agriculture, the measurement of Gini values for yields could substantially contribute to research on societal structuring. Our study provides valuable insights into the progression and transformation of irrigation practices, as well as their influence on the development of irrigated societies in the region of ancient Southern Mesopotamia.

Conclusion and Outlook

We presented our irrigation-related agent-based model $IRABM^3$ to illustrate how patterns in irrigation systems can emerge from decisions made by heterogeneous agents. We demonstrate how various factors such as irrigation demand, river discharge, and gate capacity can shape the dynamics of these systems. Importantly, our model is designed to be flexible and adaptable, enabling its application to a wide range of irrigation systems, both historical and contemporary. Through our computational approach, we contribute to discussions surrounding the development of ancient societies in Southern Mesopotamia. Our sensitivity analysis demonstrates that the most influential factors affecting yields and the decision-making are river discharge, gate capacity, farms' location, and the consequences resulting from decisions. Furthermore, our analysis suggests that the actions on farms and along canals may tend more towards realism than boldness for systems that have a longer-term existence. These findings align with intuition and illustrate the feasibility and robustness of using agent-based modelling to simulate an irrigation system.

The outcomes of our research on expansion patterns and movement patterns shed light on the varying impacts on farms and the irrigation system as a whole. We observed how farms located upstream and downstream can engage in checks and balances due to disparities in water availability resulting from decision-making at different levels. Our findings emphasize that while farms may prioritize their own interests when making decisions, these choices can have adverse effects on other farms. Similarly, collective decision-making regarding irrigation management can yield benefits for the overall system or part of farms but may also affect yields at farm level. We also demonstrated how agents' decision-making and interactions contribute to the evolution of the irrigation system (or irrigated landscape). We applied the Gini coefficient to assess the yields inequality among farms, with Gini values exhibiting fluctuations that correspond to the progression of the irrigation system over a span of 100 years. When considering a larger time frame spanning thousands of years, the irrigation system in Southern Mesopotamia experienced gradual growth. The area underwent cycles of formulation, establishment, stability, and subsequent rounds of formulation, establishment, and stability. Our findings offer a reflection of the inequality in barley yields among farms and can provide valuable insights into the evolutionary trajectory of irrigation-based societies in Southern Mesopotamia, when further developed.

Southern Mesopotamia witnessed an expanding irrigated landscape, characterized by an increasing number of agricultural units over a long period of time. In our forthcoming research, we aim to extend the time scale of the irrigation system's evolution from one century to several millennia and also extend the spatial scale from 22 farms to fully developed irrigated landscapes with thousands of farms, enabling a deeper understanding of societal development. Specifically, we will investigate how the irrigated landscapes originated from smaller areas (associated with simple crevasses) and gradually transformed into larger areas (associated with fully developed hydraulic landscapes). To enhance the realism of our irrigation-related agent-based model, we propose incorporating additional (empirical) data, such as direct communication among farms, family cereal consumption, and farms' adaptive measures. We also aim to introduce communication between farms and areas/canals in terms of trade. This approach would not only improve the simulation of farms' activities but also facilitate the validation process. Abandonment of farms may have occurred because of the challenges that cultivators faced, for example in terms of water availability. Furthermore, over the course of time, farms encountered challenges such as soil salinization and silting in both canals and farmlands during their irrigation endeavours. Our subsequent studies could incorporate such issues that farms confronted by providing additional constraints on crop growth in the model, offering valuable insights into the resilience of irrigation agriculture within this region—as salinity and sediments may possibly affect movement decisions as well. Hydrological data and meteorological data could also be considered to understand how water and humans interacted, shaped, and influenced each other in ancient Southern Mesopotamia. Farm abandonment may actually also result from successful irrigation: as soon as yields of irrigated agriculture are higher than required to feed a population, some (groups of) cultivators may decide to abandon farming and focus on other productive activities (like pottery) and/or societal services (like religious activities). Such choices would have been especially possible in circumstances with well-developed trade relations between areas. Thus, the study of irrigated landscapes' dynamics in Mesopotamia necessitates the exploration of both farm expansion and farm abandonment, which are intricate decisions shaped by a multitude of factors encompassing economic, environmental, and social dimensions. The comprehensive consideration of these factors is pivotal for facilitating a thorough exploration of farm dynamics to further develop our understanding of ancient Southern Mesopotamia.

Appendix 1. List of terms

River Discharge (RD): this is the capacity of the main river, WU/tick.
Gate Capacity (GC): gate structure belongs to farms and is used to transfer water from canals to farmlands. Each gate has its own capacity, WU/tick.
Initial Gate Capacity (IGC): all the GCs start at the same value for the model initialization, even with the newly expanded farms, WU/tick. The IGC of this model is 200 WU/tick.
Gate Capacity Adjustment: when there is a poor harvest situation along the canal, the collective action is to adjust the GC of upstream farms and midstream farms. The adjustment does not adjust once but probably many times depending on the evaluated yields.
Upstream Gate Capacity (UGC): the GC of upstream farms after the GC adjustment, WU/tick.
Middle stream Gate Capacity (MGC): the GC of middle stream farms after the GC adjustment, WU/tick.
Gate Capacity Variation (GCV): the time used to keep the new UGC and MGC after the adjustment, year. In this research, we set GCV = 1 year and 2 years, which means the model evaluates the yields every year or every two years to see if the GC adjustment is needed again or not.
Head Gate: gate structure at the head of the canal, it is a water distribution structure used to transfer water from the river to canals or from canals to the next level of canals.
Memory of Harvest Barley and Memory of Available Water (M): the memory of yields in the past years of each farm and the memory of received water in the past years of each farm, year. These two memories are always consistent. We set 10 years and 20 years in this model. These are factors used for decision-making in farmlands dynamics.
Expansion Year Level (EYL): the expansion years of new farms under all combinations of RDs and GCs are too complex for visualisation. In order to make the figures clearer to readers, we divided the simulated 100 years into five levels, the details are shown in the Note of Fig. 10.

Appendix 2. New farms expansion year

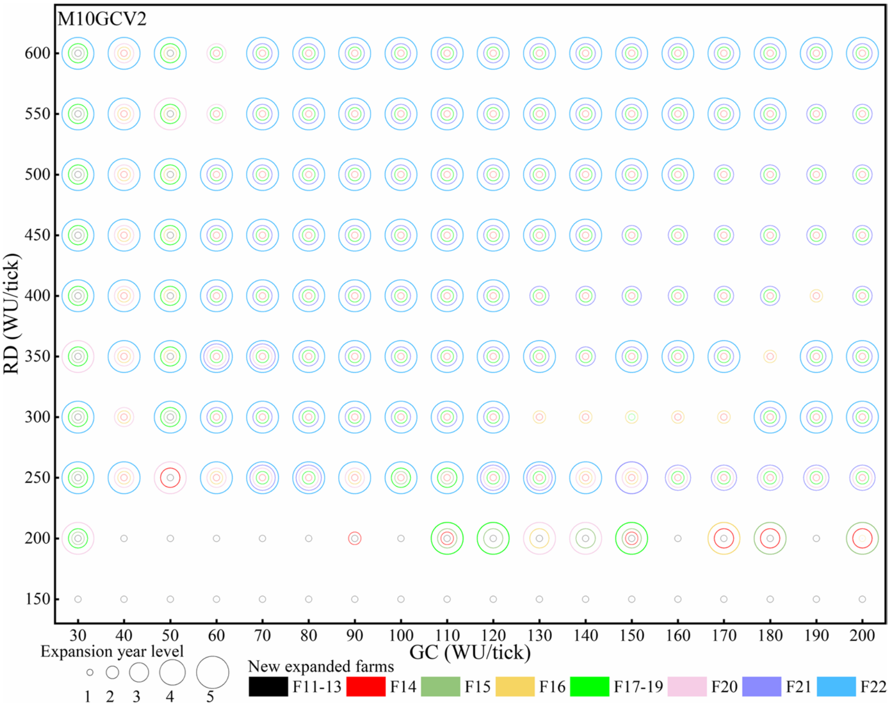

Fig. 14 The expansion year of new farms when M = 10 years, GCV = 2 year

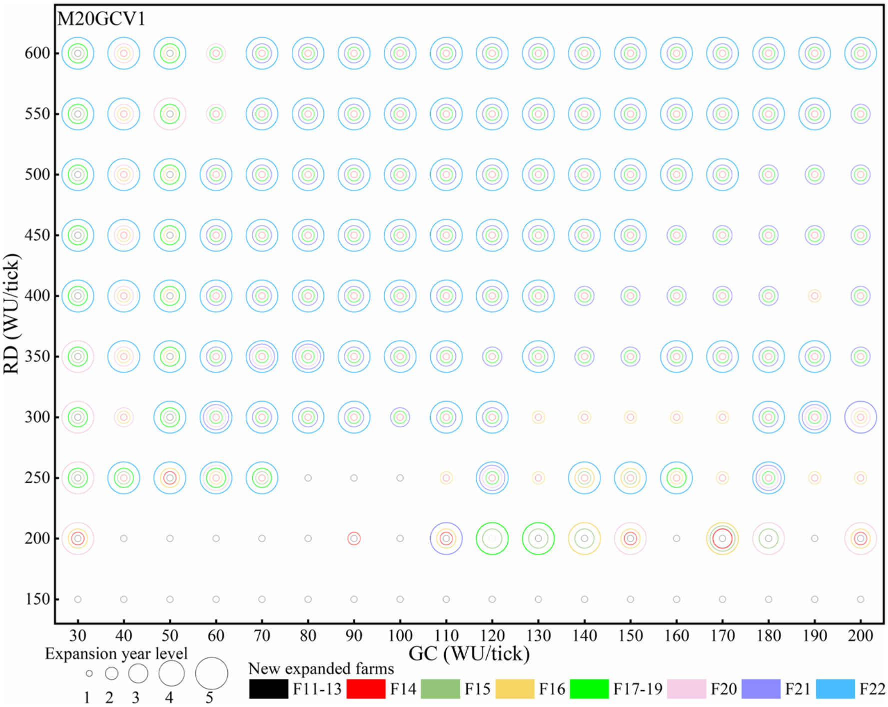

Fig. 15 The expansion year of new farms when M = 20 years, GCV = 1 year

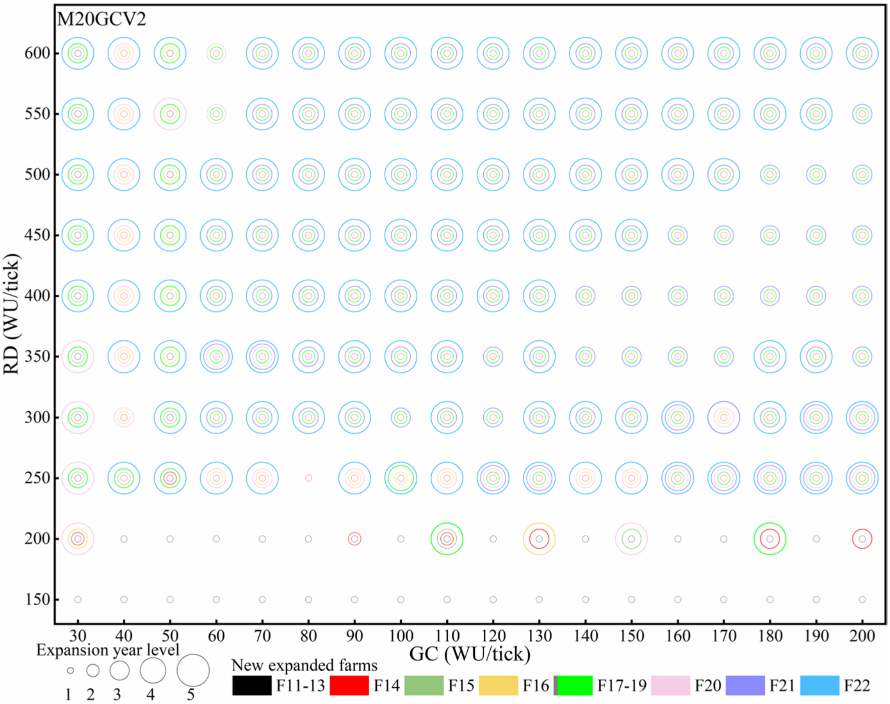

Fig. 16 The expansion year of new farms when M = 20 years, GCV = 2 year

Appendix 3. Barley yields Gini coefficient with other GCs in 100 years

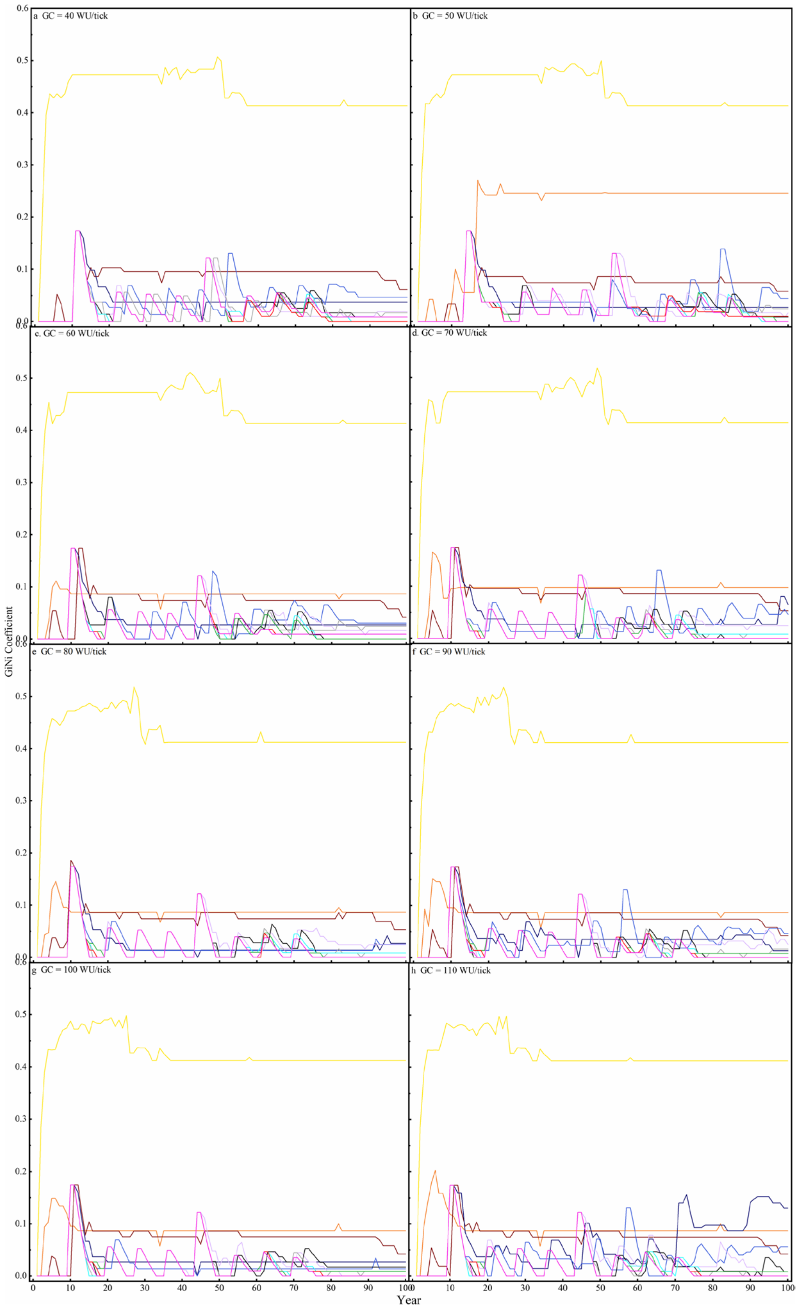

Fig. 17 Barley yields Gini coefficient with other GCs in 100 years

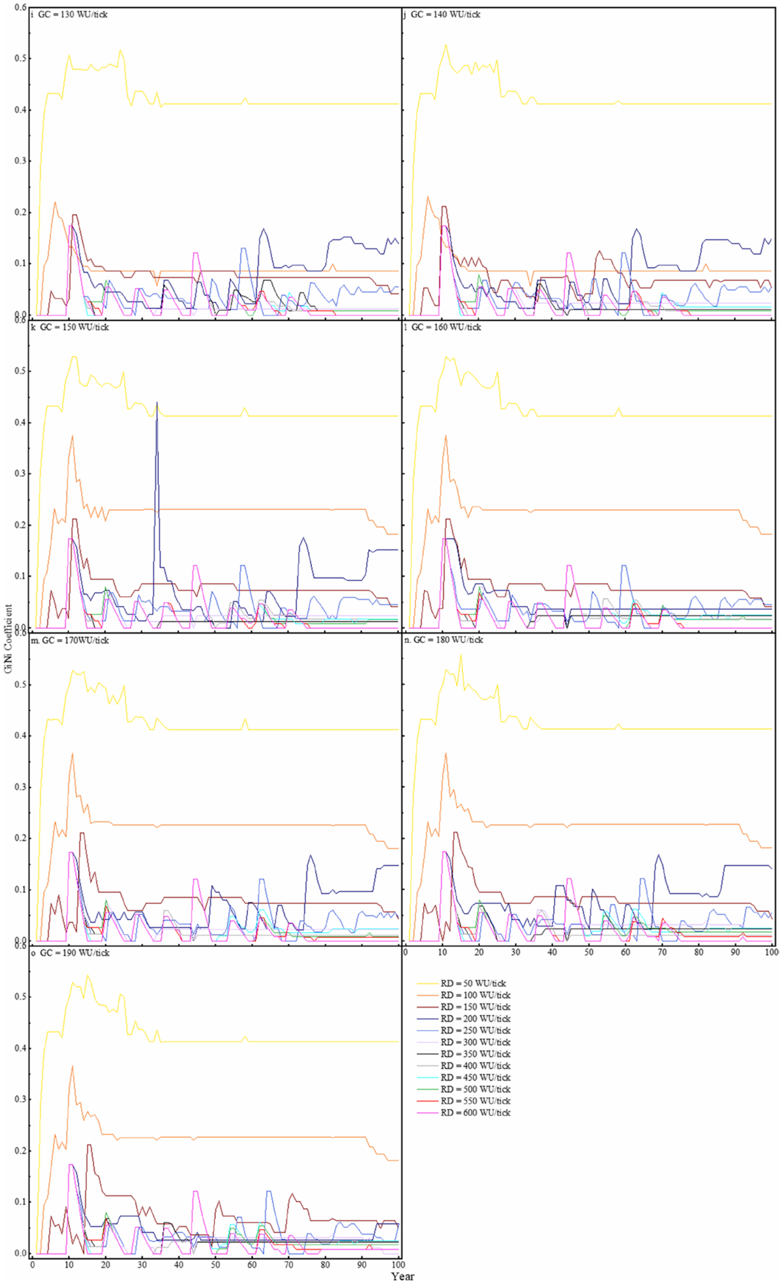

Fig. 17 (continued)

Author Contribution *DL*: conceptualization, methodology, formal analysis, visualization, and writing—original draft preparation. *MWE*: supervision, conceptualization, methodology, and writing—review and editing.

Funding This work was supported by the China Scholarship Council with the project reference number of 201806910044.

Code/Data Availability The source code for the agent-based model and data used in this analysis can be requested via email to Dengxiao Lang (D.Lang-1@tudelft.nl) until a more permanent availability has been realized.

Declarations

Competing Interests The authors declare no competing interests.

References

Adams, R. M. (1965). *Land behind Baghdad: A history of settlement on the Diyala Plains*. University of Chicago Press.

Adams, R. M. (1981). *Heartland of cities. Technology and culture*. Chicago, IL: University of Chicago Press. https://doi.org/10.2307/3104772

Aghaie, V., Alizadeh, H., & Afshar, A. (2020). Agent-based hydro-economic modelling for analysis of groundwater-based irrigation water market mechanisms. *Agricultural Water Management, 234*(March), 106140. https://doi.org/10.1016/j.agwat.2020.106140

Alam, M. F., McClain, M., Sikka, A., & Pande, S. (2022). Understanding human-water feedbacks of interventions in agricultural systems with agent based models: A review. *Environmental Research Letters*, *17*(10). https://doi.org/10.1088/1748-9326/ac91e1

Albiac, J., Calvo, E., Kahil, T., & Esteban, E. (2020). The challenge of irrigation water pricing in the water framework directive. *Water Alternatives, 13*(3), 674–690.

Alexander, M., & Violet, W. (2012). Trade and traders of Mesopotamian Ur. *Proceedings of ASBBS, 19*(1), 12–17.

Altaweel, M., & Watanabe, C. E. (2012). Assessing the resilience of irrigation agriculture: applying a social-ecological model for understanding the mitigation of salinization. *Journal of Archaeological Science, 39*(4), 1160–1171. https://doi.org/10.1016/j.jas.2011.12.020

Altaweel, M. (2019). Southern Mesopotamia: Water and the rise of urbanism. *Wiley Interdisciplinary Reviews: Water*, (April), e1362. https://doi.org/10.1002/wat2.1362

An, L. (2012). Modeling human decisions in coupled human and natural systems: review of agent-based models. *Ecological Modelling, 229*, 25–36. https://doi.org/10.1016/j.ecolmodel.2011.07.010

Anthony, P., & Birendra, K. C. (2018). Improving irrigation water management using agent technology. *New Zealand Journal of Agricultural Research, 61*(4), 425–439. https://doi.org/10.1080/00288233.2017.1402788

Arnall, A. (2014). A climate of control: Flooding, displacement and planned resettlement in the Lower Zambezi River valley. *Mozambique. Geographical Journal, 180*(2), 141–150. https://doi.org/10.1111/geoj.12036

Bahrami, N., Afshar, A., & Afshar, M. H. (2022). An agent-based framework for simulating interactions between reservoir operators and farmers for reservoir management with dynamic demands. *Agricultural Water Management, 259*(October 2021), 107237. https://doi.org/10.1016/j.agwat.2021.107237

Baker, H. D. (2022). *The later phases of southern Mesopotamian urbanism: Babylonia in the second and first millennia BC. Journal of Archaeological Research* (Vol. 31). Springer US. https://doi.org/10.1007/s10814-022-09174-8

Bar-Matthews, M., Ayalon, A., Kaufman, A., & Wasserburg, G. J. (1999). The Eastern Mediterranean paleoclimate as a reflection of regional events: Soreq cave, Israel. *Earth and Planetary Science Letters, 166*(1–2), 85–95. https://doi.org/10.1016/S0012-821X(98)00275-1

Basri, P., & Lawrence, D. (2020). Wealth Inequality in the Ancient near East: a preliminary assessment using Gini coefficients and household size. *Cambridge Archaeological Journal, 30*(4), 689–704. https://doi.org/10.1017/S0959774320000177

Becu, N., Perez, P., Walker, A., Barreteau, O., & Le Page, C. (2003). Agent based simulation of a small catchment water management in northern Thailand description of the CATCHSCAPE model. *Ecological Modelling, 170*(2–3), 319–331. https://doi.org/10.1016/S0304-3800(03)00236-9

Bell, A., Parkhurst, G., Droppelmann, K., & Benton, T. G. (2016). Scaling up pro-environmental agricultural practice using agglomeration payments: proof of concept from an agent-based model. *Ecological Economics, 126*, 32–41. https://doi.org/10.1016/j.ecolecon.2016.03.002

Brughmans, T., Hanson, J. W., Mandich, M. J., Romanowska, I., Rubio-Campillo, X., & Carrignon, S. et al. (2019). Formal modelling approaches to complexity science in Roman studies: a manifesto. *Theoretical Roman Archaeology Journal*, *2*(1). https://doi.org/10.16995/traj.367

Brughmans, T., & Poblome, J. (2016). Mercury: An agent-based model of tableware trade in the Roman east. *Jasss, 19*(1), 1–18. https://doi.org/10.18564/jasss.2953

Buringh, R. P. (1960). *Soils and soil conditions in Iraq*. The Ministry of Agriculture, Baghdad, p 337

Campano, F., & Salvatore, D. (2006). *Income Distribution.* Oxford University Press; 2006. https://www.EconPapers.repec.org/RePEc:oxp:obooks:9780195300918

Carrignon, S., Brughmans, T., & Romanowska, I. (2020). Tableware trade in the Roman East: exploring cultural and economic transmission with agent-based modelling and approximate Bayesian computation. *PLoS One, 15*(11 November), 1–23. https://doi.org/10.1371/journal.pone.0240414

Collar, A., Coward, F., Brughmans, T., & Mills, B. J. (2015). *Networks in archaeology: Phenomena, abstraction, representation*. *Journal of Archaeological Method and Theory* (Vol. 22). https://doi.org/10.1007/s10816-014-9235-6

de Bruijn, J. A., Smilovic, M., Burek, P., Guillaumot, L., Wada, Y., Aerts, J. (2023). GEB v0.1: A large-scale agent-based socio-hydrological model-simulating10 million individual farming households in a fully distributed hydrological model. *Geoscientific Model Development, 16*, 2437–2454. https://doi.org/10.5194/gmd-16-2437-2023

D'Exelle, B., Lecoutere, E., & Van Campenhout, B. (2012). Equity-efficiency trade-offs in irrigation water sharing: evidence from a field lab in Rural Tanzania. *World Development, 40*(12), 2537–2551. https://doi.org/10.1016/j.worlddev.2012.05.026

D'Odorico, P., Chiarelli, D. D., Rosa, L., Bini, A., Zilberman, D., & Rulli, M. C. (2020). The global value of water in agriculture. *Proceedings of the National Academy of Sciences of the United States of America, 117*(36), 21985–21993. https://doi.org/10.1073/pnas.2005835117

Davies, M. I. J., Kipruto, T. K., & Moore, H. L. (2014). Revisiting the irrigated agricultural landscape of the Marakwet, Kenya: tracing local technology and knowledge over the recent past. *Azania, 49*(4), 486–523. https://doi.org/10.1080/0067270X.2014.979527

De Maio, F. G. (2007). Income inequality measures. *Journal of Epidemiology and Community Health, 61*(10), 849–852. https://doi.org/10.1136/jech.2006.052969

DeAngelis, D. L., & Diaz, S. G. (2019). Decision-making in agent-based modeling: A current review and future prospectus. *Frontiers in Ecology and Evolution, 6*(JAN), 1–15. https://doi.org/10.3389/fevo.2018.00237

Dury, J. Ô., Garcia, F., Reynaud, A., & Bergez, J. E. (2013). Cropping-plan decision-making on irrigated crop farms: a spatio-temporal analysis. *European Journal of Agronomy, 50*, 1–10. https://doi.org/10.1016/j.eja.2013.04.008

Edens, C. (1992). Dynamics of trade in the ancient Mesopotamian "world system." *American Anthropologist, 94*(1), 118–139. https://doi.org/10.1525/aa.1992.94.1.02a00070

Ellison, R. (1981). Diet in Mesopotamia: The evidence of the barley ration texts (c. 3000–1400 BC). *Iraq, 43*(1), 35–45.

Elsawah, S., Guillaume, J. H. A., Filatova, T., Rook, J., & Jakeman, A. J. (2015). A methodology for eliciting, representing, and analysing stakeholder knowledge for decision making on complex socio-ecological systems: from cognitive maps to agent-based models. *Journal of Environmental Management, 151*, 500–516. https://doi.org/10.1016/j.jenvman.2014.11.028

Ertsen, M. W. (2010). Structuring properties of irrigation systems: understanding relations between humans and hydraulics through modeling. *Water History, 2*(2), 165–183. https://doi.org/10.1007/s12685-010-0023-2

Ertsen, M. W. (2016). 'Friendship is a slow ripening fruit': An agency perspective on water, values and infrastructure. *World Archaeology, 48*(4), 500–516. https://doi.org/10.1080/00438243.2016.1246975

Ertsen, M. W., Murphy, J. T., Purdue, L. E., & Zhu, T. (2014). A journey of a thousand miles begins with one small step-human agency, hydrological processes and time in socio-hydrology. *Hydrology and Earth System Sciences, 18*(4), 1369–1382. https://doi.org/10.5194/hess-18-1369-2014

Filatova, T., Verburg, P. H., Parker, D. C., & Stannard, C. A. (2013). Spatial agent-based models for socio-ecological systems: challenges and prospects. *Environmental Modelling and Software, 45*, 1–7. https://doi.org/10.1016/j.envsoft.2013.03.017

Foldvari, P., & Van Leeuwen, B. (2012). Comparing per capita income in the hellenistic world: the case of mesopotamia. *Review of Income and Wealth, 58*(3), 550–568. https://doi.org/10.1111/j.1475-4991.2011.00473.x

Geertz, C. (1972). The wet and the dry: traditional irrigation in Bali and Morocco. *Human Ecology, 1*(1), 23–39. https://doi.org/10.1007/BF01791279

Gini, C. W. (1912). *Variability and mutability, contribution to the study of statistical distributions and relations*. Universita de Cagliari.

Gomez-Zavaglia, A., Mejuto, J. C., & Simal-Gandara, J. (2020). Mitigation of emerging implications of climate change on food production systems. *Food Research International, 134*(March), 109256. https://doi.org/10.1016/j.foodres.2020.109256

Graham, S., Brughmans, T., & Romanowska, I. (2022). On building FORVM: Making our research on the Roman economy playable...and fun. *Re-Rolling the Past: Representations and Reinterpretations of Antiquity in Analog and Digital Games. ISAW Papers 22.3, 3*, 1–10. https://www.hdl.handle.net/2333.1/ncjsxxs1. Accessed 17 Jul 2023

Gras, C. (2009). Changing patterns in family farming: the case of the pampa region, Argentina. *Journal of Agrarian Change, 9*(3), 345–364. https://doi.org/10.1111/j.1471-0366.2009.00215.x

Harch, B. D., Correll, R. L., Meech, W., Kirkby, C. A., & Pankhurst, C. E. (1997). Using the Gini coefficient with BIOLOG substrate utilisation data to provide an alternative quantitative measure for comparing bacterial soil communities. *Journal of Microbiological Methods, 30*(1), 91–101. https://doi.org/10.1016/S0167-7012(97)00048-1

Helbaek, H. (1959). Domestication of food plants in the Old World. *Science, 130*(3372), 365–372.

Heppenstall, A., Crooks, A., Malleson, N., Manley, E., Ge, J., & Batty, M. (2021). Future developments in geographical agent-based models: challenges and opportunities. *Geographical Analysis, 53*(1), 76–91. https://doi.org/10.1111/gean.12267

Holman, I. P., Brown, C., Carter, T. R., Harrison, P. A., & Rounsevell, M. (2019). Improving the representation of adaptation in climate change impact models. *Regional Environmental Change, 19*(3), 711–721. https://doi.org/10.1007/s10113-018-1328-4

Hritz, C. (2010). Tracing settlement patterns and channel systems in southern Mesopotamia using remote sensing. *Journal of Field Archaeology, 35*(2), 184–203. https://doi.org/10.1179/009346910X12707321520477

Hyun, J. Y., Huang, S. Y., Yang, Y. C. E., Tidwell, V., & Macknick, J. (2019). Using a coupled agent-based modeling approach to analyze the role of risk perception in water management decisions. *Hydrology and Earth System Sciences, 23*(5), 2261–2278. https://doi.org/10.5194/hess-23-2261-2019

Jacobsen, T., & Adams, R. M. (1958). Salt and silt in ancient mesopotamian agriculture. *Science, 128*(3334), 1251–1258. https://doi.org/10.1126/science.128.3334.1251

Jotheri, J. (2016). Holocene avulsion history of the Euphrates and Tigris rivers in the Mesopotamian Floodplain. (PhD dissertation). Durham University

Kaiser, K. E., Flores, A. N., & Hillis, V. (2020). Identifying emergent agent types and effective practices for portability, scalability, and intercomparison in water resource agent-based models. *Environmental Modelling and Software, 127*(July 2019), 104671. https://doi.org/10.1016/j.envsoft.2020.104671

Kohler, T. A., Smith, M. E., Bogaard, A., Feinman, G. M., Peterson, C. E., Betzenhauser, A., et al. (2017). Greater post-Neolithic wealth disparities in Eurasia than in North America and Mesoamerica. *Nature, 551*(7682), 619–622. https://doi.org/10.1038/nature24646

Lang, D., & Ertsen, M. W. (2022a). Agent-based modelling to understand irrigated farmland dynamics and farmer decision-making. *IFAC-PapersOnLine, 55*(5), 18–24. https://doi.org/10.1016/j.ifacol.2022.07.633

Lang, D., & Ertsen, M. W. (2022b). Conceptualising and implementing an agent-based model of an irrigation system. *Water, 14*(16), 2565. https://doi.org/10.3390/w14162565

Lemcke, G., & Sturm, M. (1997). δ18o and trace element measurements as proxy for the reconstruction of climate changes at Lake Van (Turkey): Preliminary results. *Third Millennium BC Climate Change and Old World Collapse*, (January 1997), 653–678. https://doi.org/10.1007/978-3-642-60616-8_29

Li, D., Zhao, J., & Govindaraju, R. S. (2019). Water benefits sharing under transboundary cooperation in the Lancang-Mekong River Basin. *Journal of Hydrology, 577*(March), 123989. https://doi.org/10.1016/j.jhydrol.2019.123989

Ligmann-Zielinska, A., Kramer, D. B., Cheruvelil, K. S., & Soranno, P. A. (2014). Using uncertainty and sensitivity analyses in socioecological agent-based models to improve their analytical performance and policy relevance. *PLoS One*, *9*(10). https://doi.org/10.1371/journal.pone.0109779

Lorenz, M. O. (1905). Methods of measuring the concentration of wealth. *Publications of the American Statistical Association, 9*(70), 209–219. https://doi.org/10.1080/15225437.1905.10503443

Marques, G. F., Lund, J. R., Leu, M. R., Jenkins, M., Howitt, R., Harter, T., et al. (2006). Economically driven simulation of regional water systems: Friant-Kern, California. *Journal of Water Resources Planning and Management, 132*(6), 468–479. https://doi.org/10.1061/(asce)0733-9496(2006)132:6(468)

Meempatta, L., Webb, A. J., Horne, A. C., Keogh, L. A., Loch, A., & Stewardson, M. J. (2019). Reviewing the decision-making behavior of irrigators. *Wiley Interdisciplinary Reviews: Water, 6*(5), 1–29. https://doi.org/10.1002/WAT2.1366

Merot, A., Bergez, J. E., Capillon, A., & Wery, J. (2008). Analysing farming practices to develop a numerical, operational model of farmers' decision-making processes: an irrigated hay cropping system in France. *Agricultural Systems, 98*(2), 108–118. https://doi.org/10.1016/j.agsy.2008.05.001

Mezgebo, G. K., Gebrezgiabher, T. N., Gebreyesus, M. A., Gebrezgiabher, K. T., Weldegiwergis, L. G., & Hailu, H. G. (2022). Impact of community-based exclosure to smallholder farmers' livelihood and their willingness to pay: empirical evidences from Tigrai, Ethiopia. *Environment, Development and Sustainability, 24*(2), 2598–2615. https://doi.org/10.1007/s10668-021-01547-1

Mireille, N., & Marianne, L. B. (2007). Original article SALADPLAN : a model of the decision-making process in lettuce. *Methods, 27*, 209–221.

Murphy, J. T., Altaweel, M., Ozik, J., & Lammers, R. B. (2019). Understanding institutions for water allocation and exchange: Insights from dynamic agent-based modeling. *Wiley Interdisciplinary Reviews: Water, 6*(6), 1–11. https://doi.org/10.1002/WAT2.1384

Murphy, J. T., Ozik, J., Collier, N., Altaweel, M., Lammers, R. B., Prusevich, A. A., et al. (2015). Simulating regional hydrology and water management: An integrated agent-based approach. *Proceedings - Winter Simulation Conference*, 3913–3924. https://doi.org/10.1109/WSC.2015.7408547

Niles, M. T., Lubell, M., & Brown, M. (2015). How limiting factors drive agricultural adaptation to climate change. *Agriculture, Ecosystems and Environment, 200*, 178–185. https://doi.org/10.1016/j.agee.2014.11.010

Ostrom, E., & Gardner, R. (1993). Coping with asymmetries in the commons: self-governing irrigation systems can work. *Journal of Economic Perspectives, 7*(4), 93–112. https://doi.org/10.1257/jep.7.4.93

Ozik, J., Collier, N., Murphy, J. T., Altaweel, M., Lammers, R. B., Prusevich, A. A., et al. (2014). Simulating water, individuals, and management using a coupled and distributed approach. *Proceedings—Winter Simulation Conference*, (Kenney 1997), 1120–1131. https://doi.org/10.1109/WSC.2014.7019970

Perry, G. L. W., & O'Sullivan, D. (2018). Identifying narrative descriptions in agent-based models representing past human-environment interactions. *Journal of Archaeological Method and Theory, 25*(3), 795–817. https://doi.org/10.1007/s10816-017-9355-x

Piketty, T., & Saez, E. (2014). Income inequality in Europe and the United States. *Science, 344*(6186), 838–843. https://doi.org/10.1162/00335530360535135

Pluchinotta, I., Pagano, A., Giordano, R., & Tsoukiàs, A. (2018). A system dynamics model for supporting decision-makers in irrigation water management. *Journal of Environmental Management, 223*(December 2017), 815–824. https://doi.org/10.1016/j.jenvman.2018.06.083

Pournelle, J. R. (2003). Marshland of cities: Deltaic landscapes and the evolution of early Mesopotamian civilization. *Zitteliana, 18*(1), 22–27. https://doi.org/10.13140/RG.2.2.34918.11847

Rasch, S., Heckelei, T., Oomen, R., & Naumann, C. (2016). Cooperation and collapse in a communal livestock production SES model—a case from South Africa. *Environmental Modelling and Software, 75*, 402–413. https://doi.org/10.1016/j.envsoft.2014.12.008

Robertson, D., & Wang, Q. J. (2004). Bayesian networks for decision analyses—an application to irrigation system selection. *Australian Journal of Experimental Agriculture, 44*(2), 145–150.

Romanowska, I., Brughmans, T., Bes, P., Carrignon, S., Egelund, L., Lichtenberger, A., & Raja, R. (2022). A study of the centuries-long reliance on local ceramics in Jerash through full quantification and simulation. *Journal of Archaeological Method and Theory, 29*(1), 31–49. https://doi.org/10.1007/s10816-021-09510-0

Rosa, L., Chiarelli, D. D., Tu, C., Rulli, M. C., & D'odorico, P. (2019). Global unsustainable virtual water flows in agricultural trade. *Environmental Research Letters*, *14*(11). https://doi.org/10.1088/1748-9326/ab4bfc

Rost, Stephanie. (2017). Water management in Mesopotamia from the sixth till the first millennium B.C. *Wiley Interdisciplinary Reviews: Water, 4*(5), e1230. https://doi.org/10.1002/wat2.1230

Rost, Stepahnie. (2015). Watercourse management and political centralization in third-millennium B . C . Southern Mesopotamia : a case study of the Umma province of the Ur III period (2112 – 2004 B . C .).

Rothman, M. S. (2004). Studying the development of complex society: mesopotamia in the late fifth and fourth millennia BC. *Journal of Archaeological Research, 12*(1), 75–119. https://doi.org/10.1023/B:JARE.0000016695.21169.37

Ruland, M., Andirkó, A., Romanowska, I., & Boeckx, C. (2023). Modelling of factors underlying the evolution of human language. *Adaptive Behavior*, *0*(0), 1–14. https://doi.org/10.1177/10597123221147336

Sadras, V., & Bongiovanni, R. (2004). Use of Lorenz curves and Gini coefficients to assess yield inequality within paddocks. *Field Crops Research, 90*(2–3), 303–310. https://doi.org/10.1016/j.fcr.2004.04.003

Sitthiyot, T., & Holasut, K. (2020). A simple method for measuring inequality. *Palgrave Communications, 6*(1), 1–9. https://doi.org/10.1057/s41599-020-0484-6

Smith, C. W. (1995). *Crop production: Evolution, history, and technology*. John Wiley & Sons.

Squitieri, A., & Altaweel, M. (2022). Empires and the acceleration of wealth inequality in the pre-Islamic Near East: an archaeological approach. *Archaeological and Anthropological Sciences*, *14*(10). https://doi.org/10.1007/s12520-022-01659-3

Streefkerk, I. N., de Bruijn, J., Haer, T., Van Loon, A. F., Quichimbo, E. A., Wens, M., et al. (2023). A coupled agent-based model to analyse human-drought feedbacks for agropastoralists in dryland regions. *Frontiers in Water*, *4*. https://doi.org/10.3389/frwa.2022.1037971

Sueyoshi, T., Qu, J., Li, A., & Liu, X. (2021). A new approach for evaluating technology inequality and diffusion barriers: The concept of efficiency Gini coefficient and its application in Chinese provinces. *Energy, 235*, 121256. https://doi.org/10.1016/j.energy.2021.121256

Tilmant, A., Goor, Q., & Pinte, D. (2009). Agricultural-to-hydropower water transfers: sharing water and benefits in hydropower-irrigation systems. *Hydrology and Earth System Sciences, 13*(7), 1091–1101. https://doi.org/10.5194/hess-13-1091-2009

Vesco, P., Kovacic, M., Mistry, M., & Croicu, M. (2021). Climate variability, crop and conflict: exploring the impacts of spatial concentration in agricultural production. *Journal of Peace Research, 58*(1), 98–113. https://doi.org/10.1177/0022343320971020

Vesco, P., Kovacic, M., & Mistry, M. (2019). Crop and conflict: Exploring the impact of inequality in agricultural production on conflict risk. *SSRN Electronic Journal*, (17). https://doi.org/10.2139/ssrn.3409745

Wens, M., Johnson, J. M., Zagaria, C., & Veldkamp, T. I. E. (2019). Integrating human behavior dynamics into drought risk assessment—a sociohydrologic, agent-based approach. *Wiley Interdisciplinary Reviews: Water, 6*(4), 1–19. https://doi.org/10.1002/wat2.1345

Wilkinson, T. J., Rayne, L., & Jotheri, J. (2015). Hydraulic landscapes in Mesopotamia: the role of human niche construction. *Water History, 7*(4), 397–418. https://doi.org/10.1007/s12685-015-0127-9

Wilkinson, T. J., & Jotheri, J. (2016). The origins of levee and levee-based irrigation in the Nippur area—southern Mesopotamia. In: M. Altaweel, & C. Hritz (Eds.), *Cycles and stages in jeeps and passats: Studies in the Ancient Near East in honour of McGuire Gibson*. Chicago, IL: University of Chicago Oriental Institute.

Zhang, X., Guo, P., Zhang, F., Liu, X., Yue, Q., & Wang, Y. (2021). Optimal irrigation water allocation in Hetao Irrigation District considering decision makers' preference under uncertainties. *Agricultural Water Management, 246*(17), 106670. https://doi.org/10.1016/j.agwat.2020.106670

Zheng, X., Xia, T., Yang, X., Yuan, T., & Hu, Y. (2013). The land Gini coefficient and its application for land use structure analysis in China. *PLoS One, 8*(10), 1–10. https://doi.org/10.1371/journal.pone.0076165

Zhu, T., Woodson, K. C., & Ertsen, M. W. (2018). Reconstructing ancient Hohokam irrigation systems in the Middle Gila River Valley, Arizona. *United States of America. Human Ecology, 46*(5), 735–746. https://doi.org/10.1007/s10745-018-0023-x