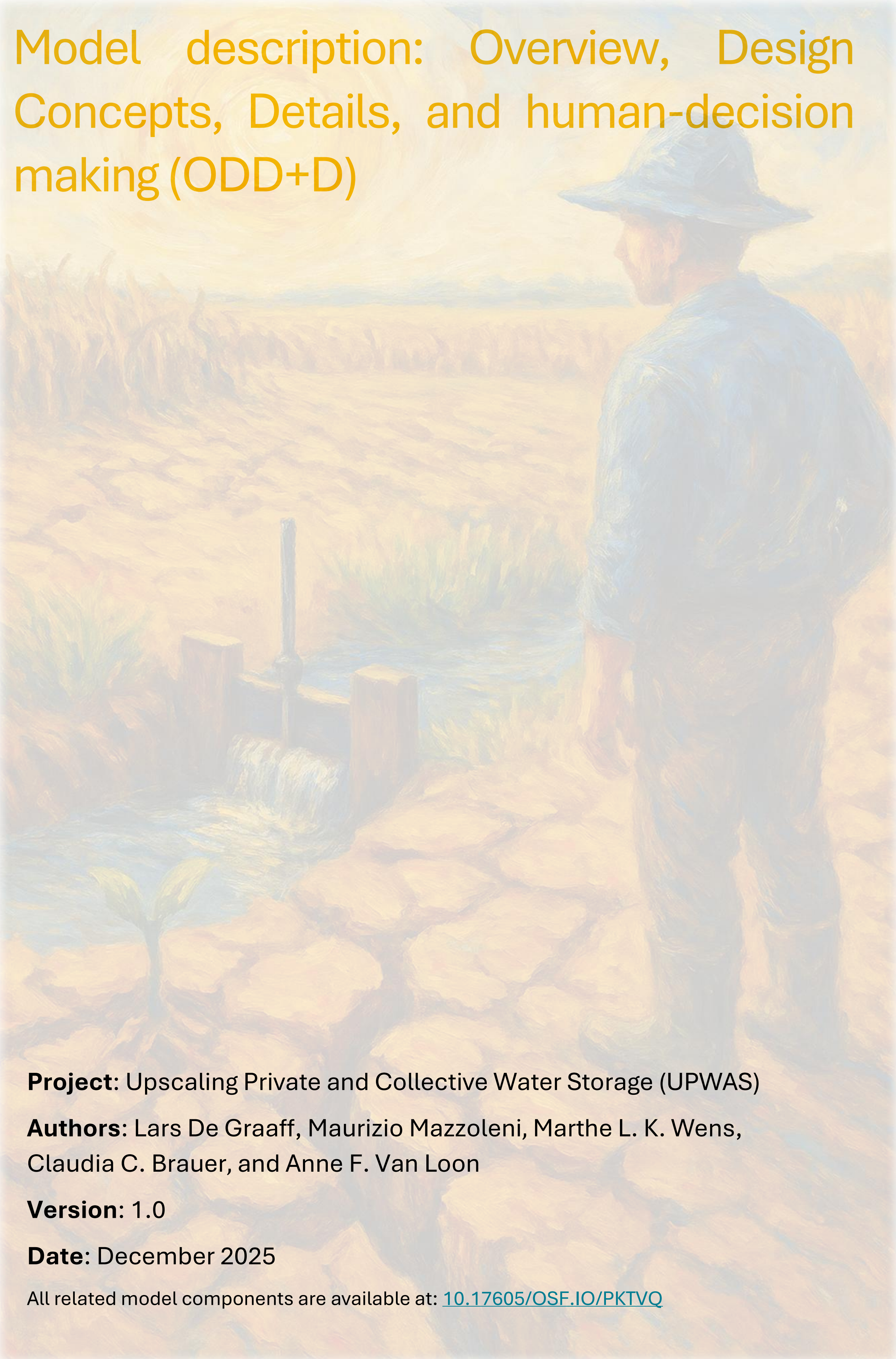

Model description: Overview, Design Concepts, Details, and human-decision making (ODD+D)

Project: Upscaling Private and Collective Water Storage (UPWAS)

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All related model components are available at: [10.17605/OSF.IO/PKTVQ](https://doi.org/10.17605/OSF.IO/PKTVQ)

Contents

1. Overview

1.1 Purpose

What is the purpose of the study?

The purpose of the model is to understand the impact of the individual adaptive behaviour of farmers on the local and regional groundwater system under different climate conditions. In this study, we explore the potential of two small-scale adaptation measures (installing adjustable weirs and reducing channel depth) to reduce drought damage. A schematic overview of the model is presented in Figure 1.

For whom is the model designed?

The model is designed for researchers to study the impact of individual adaptive behaviour on regional groundwater dynamics. Furthermore, the model can be used as a discussion tool between decision makers and farmers to discuss social and hydrological dynamics.

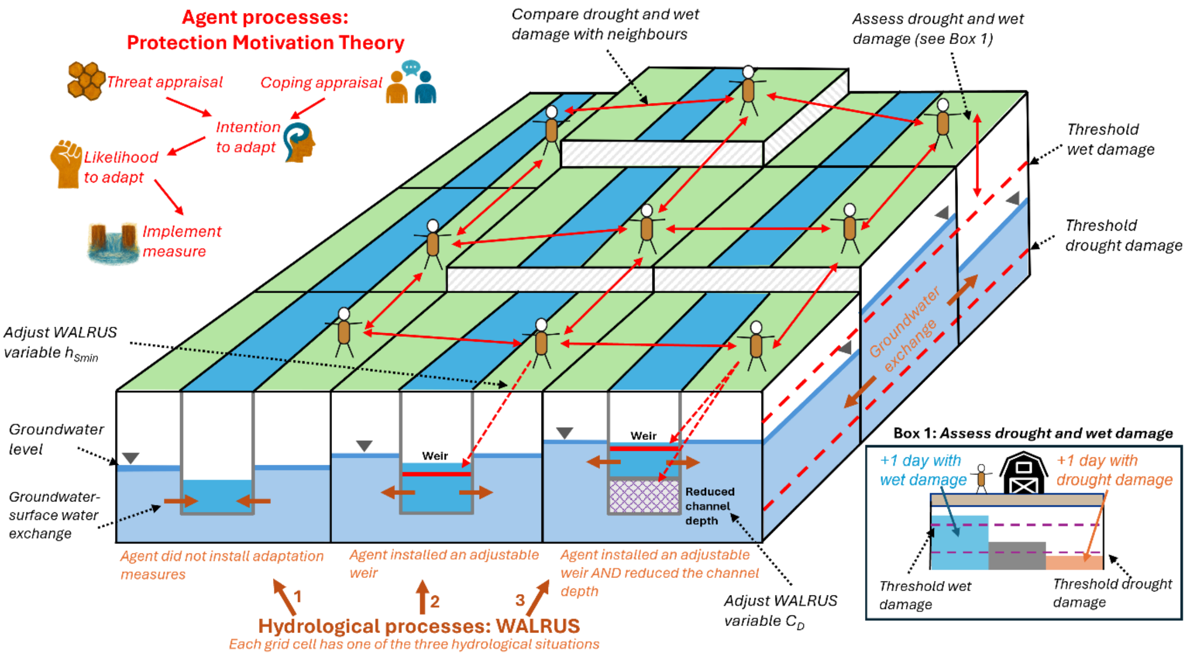

Figure 1. Schematic overview of the ABM, showing the interactions between the hydrological processes, simulated with the WALRUS hydrological model, and the agents processes, simulated with the protection motivation theory. The agents represent dairy farmers, with one agent in each grid cell. Box 1 shows how agents assess the daily drought and wet damage at the farm level (grid cell). Agents can interact with each other by comparing drought and wet damage, and agents can implement and operate adaptation measures (adjustable weirs and reduced channel depth).

1.2 Entities, state variables, and scales

What kinds of entities are in the model?

The model has one agent type, the Farmer Agent, which represents individual dairy farmers. The grid cells represent a dairy farm and can contain a maximum of one farmer agent. The environment represents a hydrological system that contains three hydrological reservoirs: soil, surface water, and quickflow.

By what attributes (i.e. state variables and parameters) are these entities characterised?

See Table 1.

What are the exogenous factors / drivers of the model?

Precipitation and potential evapotranspiration are the driving forces of the model. This study uses three different climate input files to simulate model scenarios.

How is space included in the model?

The environment has a spatially explicit grid-based distribution, with a gradual elevation difference of 10 metres from east (highest) to west (lowest). The model size is 20 by 20 grid cells and consequently contains 400 agents. Each grid cell is 800 by 800 meters to match the average dairy farm size in the Netherlands of 64 hectares (Wageningen Social and Economic Research, 2025), resulting in a total surface of 256 km^2. The model environment is based on the *Achterhoek* region in the eastern Netherlands, but does not represent an actual case study.

What are the temporal resolution and extent of the model?

The model uses a daily time step, with a total simulation time of 15 years. Each time step, the response of the hydrological system to rainfall and evaporation is simulated in each grid cell. The agents assess potential damage to their farming systems and the weir levels are adjusted. Finally, the exchange of groundwater between grid cells is computed. For each year, on the 1st of December, the agents update their perception of drought and their perceived coping abilities, which depends on the experienced drought and wet damage on their own farm and the damage situation at neighbouring farms. Based on updated behaviour variables, an agent can decide to implement an adaptation measure.

Table 1: Overview of the state variables included in the ABM

State variable	***Description***	***Value/ range***	***Unit***	***Type***
Human system:				
Age	The age of an agent	20 - 65	Years	Static
Successor	Whether agents have a farm successor, no (0), maybe (0.5), or yes (1)	0 OR 0.5 OR 1	-	Static
Drought threshold	The threshold for an agent to experience a day with drought damage	[1900 – 2100]	mm	Dynamic
Wet threshold	The threshold for an agent to experience a day with wet damage	[400 – 700]	mm	Dynamic
Mean drought stress	Yearly average experienced drought stress during the last 10 years.	[0 – 182]	days	Dynamic
Neighbourhood radius	The number of neighbouring cells that agents can see (Von Neumann)	[1 – 4]	Cells	Static
Perceived effectiveness weir	The perception of agents on how effective weirs are to mitigate drought damage	[0 – 1]	-	Dynamic
Perceived effectiveness channel	The perception of agents about how effective reduced channel depths are in minimising drought damage	[0 – 1]	-	Dynamic
Knowledge	An agents' knowledge of drought adaptation, provided by the water authority	[0 – 1]	-	Dynamic
Threat appraisal	Perceived severity of, and vulnerability to, droughts	[0 – 1]	-	Dynamic
Weir installed	Whether an agent has a weir installed (1) or not (0)	0 OR 1	-	Dynamic
Channel reduced	Whether an agent has reduced the channel depth (1) or not (0)	0 OR 1	-	Dynamic
Hydrological system:				
Channel depth (c_D)	The average depth of the channels at the agent's farm	[1200-2200]	mm	Dynamic
Bankfull discharge (c_S)	The discharge when the surface water level reaches the soil surface	cD/300	mm/h	Dynamic
Groundwater reservoir constant (c_G)	cG represents the combined effect of all resistance and variability therein	[15e6 - 20e6]	mm/h	Static
Quickflow reservoir constant (c_Q)	A time constant to calculate the flux from quickflow to surface water	[10 – 15]	h	Static
Wetness index parameter (c_W)	The value that is no moisture available in the soil	[175 – 225]	mm	Static
Transmissivity (kD)	The ability of the aquifer to transmit groundwater to neighbouring cell	[0.5e3-1.5e3]	m^2/d	Static
Groundwater depth	The depth of the groundwater level with reference to the soil surface	min: 0	mm	Dynamic
Grid cell:				
Elevation	The elevation of the grid cell with reference to sea level.	[20 – 30]	m +NAP	Static

1.3 Process overview and scheduling

What entity does what, and in what order?

The model consists of five processes that run in a daily timestep and two processes that run in a yearly timestep (Figure 2). Each process is activated with a fixed order, based on the agent's ID.

Daily processes:

1) "Update hydrological state variables": The hydrological states are updated with the WALRUS model for each agent based on daily precipitation, potential evapotranspiration, and groundwater flows of timestep *t-1*.
2) "Assess drought and wet damage": Agents compare the new depth of the groundwater with their own dry and wet thresholds to register potential drought or wet damage. If one of the thresholds is exceeded, the agent will register that day as a day with the corresponding damage type (drought/wet)
3) "Operate adjustable weir": Agents adjust their weir levels. This action is only activated if the agent has weirs installed and uses a variable operation strategy.
4) "Exchange groundwater": Agents calculate groundwater flow exchange for the time step *t+1*, based on hydrological states and elevation (grid cell property).

Yealy processes (1st of December):

5) "Update threat appraisal": Agents assess their yearly drought and wet damage which they reported in step 2. The agent updates the threat appraisal based on the yearly damage information.
6) "Update coping appraisal": Agents compare their own damage situation with the situation of neighbours to update the coping appraisal, based on the perceived effectiveness of the measures and the self-efficacy of the agents.
7) "Determine adaptation intention": The agents calculate their adaptation intention, based on the updated threat and coping appraisal, and convert this into a probability that agents will actually implement an adaptation measure.
8) "Implement measure": An agent implements a measure if the likelihood to adapt is higher than randomly drawn number (0-1) and if the farmer agent is able to receive a subsidy.

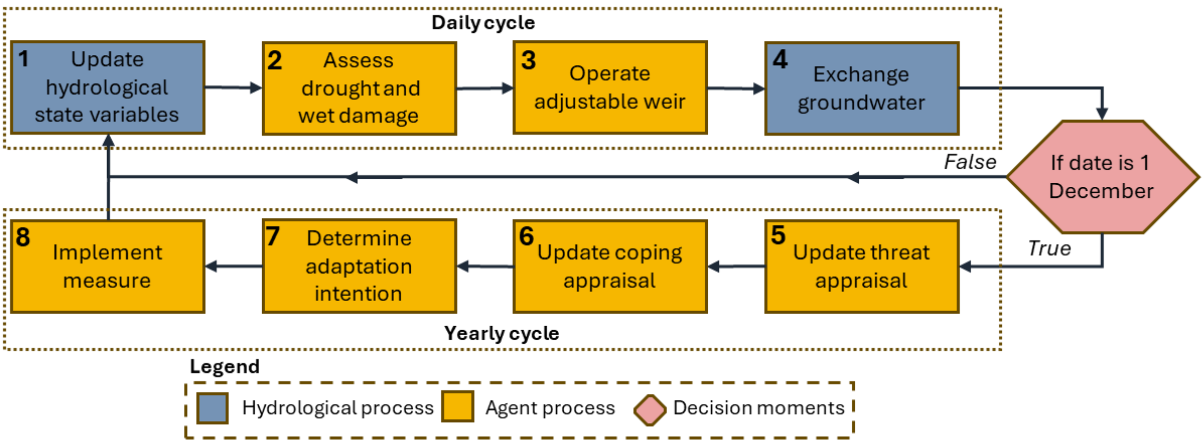

Figure 2: Overview of the step function and the scheduling of the model.

2. Design concepts

2.1 Theoretical and Empirical Background

Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the sub-model(s)?

The model is based on the concept of socio-hydrology (Sivapalan et al., 2012), in which the system level is considered as an integrated human-water system. This means that there are two-way feedbacks between the social and hydrological system. Therefore, human decision-making can influence the hydrological system, but at the same time, these decisions are also shaped by the changes in hydrological system.

On what assumptions is/are the agents' decision model(s) based?

First, we use the protection motivation theory (PMT; Rogers, 1983) as a decision model to simulate adaptive behaviour of the agents. This theory describes a person's intention to act upon a threat, which depends on the their perception of the threat (threat appraisal) and their perceived abilities to implement the protective behaviour (coping appraisal). According to the PMT, a person's threat appraisal depends on how they perceive their own vulnerability to the threat and their expected severity of the threat. Moreover, the coping appraisal depends on the perceived cost of the protective behaviour, the perceived effectiveness of this behaviour, and the perceived self-efficacy of a person to implement the protective behaviour. In this ABM, we apply the PMT to describe the protective behaviour of farmers to act upon increasing drought risk by implementing adaptation measures.

Second, someone's intention to act upon a threat does not always lead to the actual implantation of adaptation behaviour, which is known as the intention-behaviour gap (Sheeran & Webb, 2016). This assumption is included in our ABM by adding an additional step between the intention and implementation, defined as the likelihood to adapt.

Why is a/are certain decision model(s) chosen?

Human behaviour is complex and messy and does not follow rational economic decisions (Findlater et al., 2019). Therefore, we apply bounded rational behaviour in our model to simulate decision-making based on what people perceive as a satisfactory solution, rather than completely rational decisions. This assumption was initially based on the empirical results of Van Duinen et al. (2015) in the southeast of the Netherlands and later tested in the study area (eastern Netherlands) by De Graaff et al. (2025). Furthermore, farmers in the study area on which this ABM is based have access to subsidies to eliminate or minimise financial barriers, making their decision less dependent on economic incentives.

Another reason to implement this decision model was the application of PMT in ABMs by other studies, for example by Hailegiorgis et al. (2018), Streefkerk et al. (2023), Van Duinen et al. (2016), and Wens et al. (2022). These studies have highlighted the importance of adding bounded rational behaviour instead of rational decision models.

If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?

Decision model: The implementation of the PMT in the ABM is based on survey, interview, and discussion data by De Graaff et al. (2025). This data includes 85 survey responses on how farmers perceive the past, current and future drought risk, their experiences with drought adaptation, and their intention to implement adaptation measures in the near future. The interviews with farmers and the discussions with experts from the regional water authorities are used to design and conceptualise the system context of model.

Hydrological model: Groundwater timeseries of five monitoring wells in the *Hupsel Brook* catchment were extracted from the water data portal of *Waterschap Rijn & IJssel* (https://waterdata.wrij.nl/). The data consist of daily groundwater depth below the surface level for the period 2010-2024.

Additionally, daily precipitation and potential evaporation data from the KNMI Hupsel weather station (station number 668) was extracted from the KNMI Data Platform (https://dataplatform.knmi.nl/). These data were used to represent the current climate conditions of the study area for the years 2010-2024. This period contains four extremely dry years (2018-2020, 2022) and one extremely wet year (2024).

At which level of aggregation were the data available?

- Survey data is available for individual farmers in the year 2023.
- Groundwater time series and weather data are available with a daily resolution for the years 2010-2024.

2.2 Individual Decision Making

What are the subjects and objects of decision-making? On which level of aggregation is decision-making modelled?

Individual farmer agents update their PMT components (threat appraisal, coping appraisal, intention to adapt) based on the experienced drought and wet damage at the farm level (own grid cell), the damage at neighbouring farms (grid cells within neighbourhood radius), and whether an adaptation measure is implemented by the agents itself or a neighbour. The operation of the adjustable weirs (one of the adaptation options) depends on the groundwater levels at the agents own cell and the expected rainfall for the next seven days.

What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?

The agents behave within a bounded rational approach, which allows the agents to make decisions based on satisfying objectives rather than rational objectives. The objective of the agents is to minimise drought damage at their farm, which can be achieved by implementing adaptation measures. To implement such a measure, the agent must feel threatened by the drought conditions and feel comfortable by the effectiveness of the adaptation measures to reduce drought damage. At the same time, agents aim to avoid waterlogging at their farm.

How do agents make their decisions?

Agents make decisions based on protection motivation theory. The agent processes are dived into six submodels. The submodels are adjusted from the functions presented in the ADOPT-AP model of Streefkerk et al. (2023). Therefore, the equations used to calculate the PMT components and the intention-behaviour gap have similar processes as the equations in the ADOPT-AP model, but were adjusted to the context of the eastern Netherlands and the available hydrological variables of the WALRUS model.

1) <u>Assess drought and wet damage</u>

In each daily time step, the agents compare the groundwater levels at the farm level with their dry and wet groundwater thresholds. When groundwater drops below the dry threshold (lower limit), drought stress occurs that can affect crop growth. The dry threshold is only assessed during the growing season (1 April - 30 September). In addition, the agent can also experience

situations when the groundwater rises above the wet threshold (upper limit), increasing the chance of waterlogging of the farm fields. Every time groundwater levels drops below the dry threshold or exceeds the wet threshold, the agent will perceive this as a day with the respective damage (drought or wet).

2) <u>Update threat appraisal</u>

Agents update their threat appraisal based on three decision rules.

1) If, in the past year, there are *more* days with *drought damage* than on average in the last 10 years, the perceived drought damage is determined based on the difference between the number of days with drought damage (*DD*) in a certain year *t* and the average number of days with drought damage over the last 10 years, divided by the number of days in the growing season (6 months; 183 days):

$$PD_t = \left(DD_t - \frac{1}{10} \sum_{i=t-10}^{t} DD_i \right) * \frac{1}{183}$$

The threat appraisal (*TA*) of the agent is calculated with:

$$TA_{t+1} = TA_t + (PD_t * TA_t)$$

2) If the agent experienced *fewer* days with *drought damage* compared to the average number of days with drought damage of the past 10 years, the agent's threat appraisal decreases by 12.5% to mimic the agent's fading memory to previous drought events. This assumption is based on the work of Wens et al. (2020) and Streefkerk et al. (2023), who used the flood risk memory of Viglione et al. (2014) since specific data on drought memory is not available.

3) If, in the past year, the agent experienced *more than 20 days* with *wet damage*, the threat appraisal decreases by (an additional) 12.5% to simulate the priority of agents to act on flood risk rather than drought risk. This assumption is based on context interviews (De Graaff et al., 2025) and expert knowledge.

3) <u>Update coping appraisal</u>

The agents compare damage with and without measures between themselves and their neighbours to update their perceived effectiveness of the adaptation measures. If the agent experienced *more* than 20 days with *wet damage* in the past year, the perceived effectiveness of adjustable weirs decreases with 10% and the perceived effectiveness of reduced channel depth decreases with 15%. Moreover, if a neighbouring agent within the neighbourhood radius has a measure installed and experienced *more* days with *wet damage* than the agent itself (with a minimum of 10 days), then the perceived effectiveness of corresponding measure decreases with 7%. These assumptions are based on the historic focus of drainage in the Netherlands and the expectation of farmers that drought adaptation might increase the chance of waterlogging.

If the agents experienced *fewer* than 20 days with *wet damage*, then the perceived effectiveness (*PE*) of measure *m* (representing either installing weirs or reducing channel depth) is calculated based on the experienced drought damage of the agent (DD_o) and the drought damage of the neighbouring agent(s) (DD_n). If the agent does not have measure *m* installed but the neighbouring agent does, the *PE* is updated for each agent within the neighbourhood radius that matches this criterion:

$$PE_{m_{t+1}} = PE_{m_t} + \left(\frac{DD_o - DD_n}{183} * PE_{m_t} \right)$$

If the agent does have measure *m* installed but the neighbouring agent does not, the *PE* is updated for each agent within the neighbourhood radius that matches this criterion:

$$PE_{m_{t+1}} = PE_{m_t} + \left(\frac{DD_n - DD_o}{183} * \ PE_{m_t}\right)$$

PE has a minimum value of 0 and a maximum value of 1.

The self-efficacy of the agents is based on the characteristics of the agent, such as their age, adaptation knowledge, and whether they have a farm successor, and the fraction of adapting neighbours near the agent. The self-efficacy (*SE*) of an agent is calculated based on two components, each with a weight of 0.5:

$$SE = \ 0.5\left(\frac{65 - (A - S * 20)}{45}\right) + \min\left(0.5\left(\frac{AN}{TN} + K\right), 1\right)$$

The first component depends on the age of the agent (*A*) and whether the agent has a successor (*S*) for the farm (Yes=1, Maybe=0.5, No=0). Agents retire at age 65; at this moment the successor takes over (A = 20) or the farm is sold to a newly initialised agent (Table 2). Therefore, an agent can work a maximum of 45 years. The second component depends on the number of adapting neighbours (*AN*), the total number of neighbours (*TN*) in the neighbourhood radius, and the obtained knowledge (*K*). Knowledge is a factor between 0 and 1 and depends on the interactions with the water authority (see below) to simulate the agent's response to education programs.

The perceived cost is not directly included in the coping appraisal of the agents, but instead functions as a binary condition which determines whether an agent can implement a measure (see Section 2.2.3.6). In the case on which this study is inspired, most farmers implement adaptation measures only when costs are subsidised. Therefore, we assume that the perceived cost of an agent depends on whether an agent receives a subsidy: there is a 75% probability that the perceived cost equals 0 (subsidy received) and a 25% probability that it equals 1 (no subsidy). This is an assumption as no data on this is currently available.

Farmers in the study area use the water authority as the main source of information for drought adaptation (De Graaff et al., 2025). To include this knowledge role of the water authority in the model, we assume that each year 5% of the agents receive information on drought adaptation. This interaction increases the agent's *PE* of the adaptation measures with 15% and increases the agent's *K* with 0.1. The quantification of the knowledge exchange is an assumption as no data on this is currently available. The maximum value of *PE* and *K* is 1.

Based on the *PE* of the measures and the *SE* of the agent, the coping appraisal (*CA*) is calculated for each measure with:

$$CA_m = \ 0.5 \ * PE_m + 0.5 * SE$$

The maximum value for the coping appraisal is 1 and the minimum value is 0.

4) <u>Determine adaptation intention</u>

The intention to adapt (*ITA*) is based on the coping appraisal (*CA*) and the threat appraisal (*TA*) of an agent and is calculated for each measure (*m*) with:

$$ITA_m = \ 0.6 * TA + \ 0.4 * CA_m$$

Threat appraisal is more important for farmers in the study area than coping appraisal (De Graaff et al., 2025). To implement this finding, we assume that the threat appraisal has a weight of 0.6 and the coping appraisal has a weight of 0.4.

We assume that the *ITA* is the probability that an agent implements the adaptation measure during the agent's working life (45 years). However, adaptation intentions do not directly lead to adaptation behaviour (Sheeran and Webb, 2016). Therefore, we convert the ITA to the Likelihood To Adapt (LTA) wit:

$$LTA_m = 1 - (1 - ITA_m)^{\frac{1}{45}}$$

LTA is the probability that the agent will actually implement the adaptation measure at timestep *t*.

5) <u>Implement measure</u>

The agent can implement measure *m* if the corresponding *LTA* is higher than a randomly drawn threshold (0-1) and the perceived cost is 0 (agent receives a subsidy). An agent first installs an adjustable weir, which allows the agent to manipulate the surface water level (see Section 2.2.3.2). If an agent already has an adjustable weir installed, the next measure they implement is reducing the channel depth. In this case the channel depth, c_D (see Section 2.1.2.1), is reduced with 25-50% of the total depth. Installing adjustable weirs will allow the farmer agent to learn and experiment with a flexible adaptation measure (adjustable weirs) before implementing a structural adaptation measure (reduced channel depth). This learning process is based on informal conversations with farmers and experts from the water authority in the study area.

6) <u>Operating adjustable weirs</u>

Agents with adjustable weirs installed can alter the weir height ($h_{S,min}$) in the channel between 0% and 80% of the total channel depth (see Figure 3). After implementation of a weir, the agent operates the weir with a standard operation strategy. This strategy represents current water management strategies in the Netherlands, with the focus on drainage in late winter/early spring to allow (heavy) machinery to access farm fields in early spring. A year after the implementation of the weir, the agent can switch to a variable operating strategy that allows the agent to adjust the weir level once a week, depending on current groundwater levels and the expected total rainfall for the next week. The expected rainfall has a maximum uncertainty of +/- 5% to account for the unpredictability in the weather forecast. Agents operate their weir on a fixed day of the week, but this day is different between the agents to allow daily changes in weir operation to

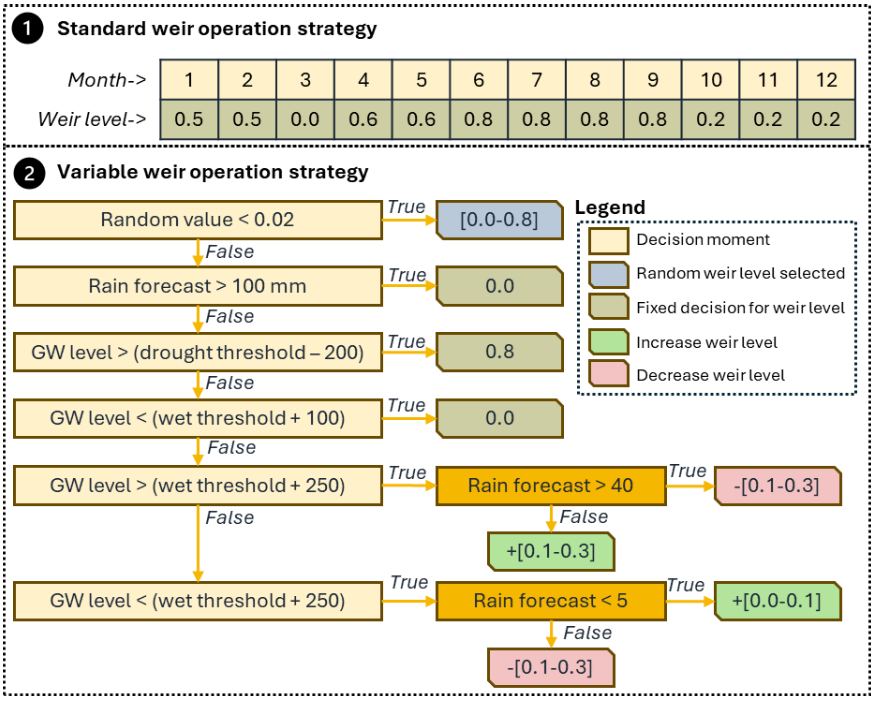

Figure 3. Operation strategies of the adjustable weirs. Agents start with at least one year with operation strategy 1. After positive experiences with the adjustable weir, the agents can decide once a year to shift to operation strategy 2 but cannot go back to operation strategy 1.

Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes, how?

Agents react to the drought and wet damage experienced on their own farm and compare this with neighbours to evaluate the effectiveness of adaptation measures.

Do social norms or cultural values play a role in the decision-making process?

Not directly, but the behaviour of the agents is based on empirical data from the study area which reflect cultural norms (e.g. focus on drainage).

Do spatial aspects play a role in the decision process?

Agents compare their own perceived damage to the damage of neighbours within the neighbourhood radius.

Do temporal aspects play a role in the decision process?

Farmer agents have a memory of the average perceived drought damage in the last 10 years. This is updated each year by taking 90 % of the original average drought damage and 10 % of the current drought damage.

To which extent and how is uncertainty included in the agents' decision rules?

A maximum of +/- 5 % uncertainty is included in the weekly weather forecast of the agents that operate the weirs with a variable operating strategy. The rest of the behaviour rules do have explicit uncertainty, but use a probability approach.

2.3 Learning

Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?

Agents learn from their own experiences and the experiences of their neighbours. The experienced drought and wet damage can increase or decrease the perception of the agent on how effective the adaptation measures are in reducing the drought damage, but also what the

potential risk for waterlogging is. An agent first needs to install an adjustable weir before they can reduce the channel depth. This allows the agent to experiment with a flexible adaptation measure before they decide to implement a structural adaptation measure.

Is collective learning implemented in the model?
There is no collective learning implemented in the model.

2.4 Individual Sensing

What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?
Agents can sense groundwater levels in their own cell and compare this with their own drought and wet threshold to assess potential drought and wet damage to their farm. Moreover, if agents use a variable weir operation strategy, they can sense total rainfall in the next 7 days with a maximum error margin of +/- 5 %.

What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?
Agents can sense the drought and wet damage of their neighbours within the neighbourhood radius and whether these neighbours implemented adaptation measures. This information is used to update the perceived effectiveness of adaptation measures. There is no error included in sensing the state variables of the neighbouring agents.

What is the spatial scale of sensing?
Each farmer agent can sense neighbours within their Von Neumann neighbourhood radius. The radius differs between agents and ranges from 1 to 4 cells.

Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?
No explicit mechanism is modelled for the agents to obtain information.

Are the costs for cognition and the costs for gathering information explicitly included in the model?
There are no costs included in the model.

2.5 Individual Prediction

Which data uses the agent to predict future conditions?
Precipitation data are used to operate the adjustable weirs.

What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?
No specific models.

Might agents be erroneous in the prediction process, and how is it implemented?
A random error of maximum +/- 5 % is used in the 7-day rain forecast that the agent is able to see when they have adopted the flexible weir operation strategy.

2.6 Interaction

Are interactions among agents and entities assumed as direct or indirect?

The interaction between agents occurs indirectly through environmental factors: drought stress, wet damage, and implemented measures.

On what do the interactions depend?

Interactions depend on the spatial distance between the agents (neighbourhood radius), whether the neighbouring agents installed adaptation measures, and the experienced drought and wet damage of the neighbours.

If the interactions involve communication, how are such communications represented?

The model does not contain explicit communication between agents.

If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?

Collaboration networks are not included.

2.7 Collectives

Do the individuals form or belong to aggregations that affect, and are affected by, the individuals?

No collectives are formed in the model.

2.8 Heterogeneity

Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

Agents are heterogeneous in the following way:

- Age
- Successor (yes/maybe/no)
- Neighbourhood radius
- Dry threshold
- Wet threshold
- Threat appraisal
- Coping appraisal for 1) weirs, and 2) reduced channel depth
- Intention to adapt for 1) weirs, and 2) reduced channel depth
- Knowledge of adaptation measures

Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?

The general decision model is the same for all agents (PMT). However, depending on the experiences with adaptation measures (weirs), an agent might be able to implement additional measures (reduce the depth of the channel).

2.9 Stochasticity

What processes (including initialisation) are modelled by assuming they are random or partly random?

Agent initialisation: Age, Successor, Drought threshold, Wet threshold, Mean drought stress, Neighbourhood radius, Perceived effectiveness weir, Perceived effectiveness channel, Knowledge, Threat appraisal, Weir installed (*based on fixed probability*), Channel reduced (*based on fixed probability*).

Hydrology initialisation: Channel depth (c_D), Groundwater reservoir constant (c_G), Quickflow reservoir constant (c_Q) , Wetness index parameter (c_W), Transmissivity (kD).

Processes:

- Knowledge of the water authority: There is 5% chance that an agent increases the perceived effectiveness of the two measures and gain knowledge if they have not installed a weir. This chance increases to 10% after the agent installed a weir.
- Receive subsidy: There is 75% chance that an agent receives a subsidy from the water authority (perceived cost = 0).
- Implement a measure: If a random drawn value between 1 and 0 is lower than the *likelihood to adapt*
- Reduce channel depth: Channel depth will be reduced with a random value between 20-50%.
- Variable weir operation: Adjusting weir levels is dependent on the processes shown in Figure 3.
- Weather forecast: A random error margin between +/- 5 % is implemented in the rainfall forecast
- Decide on successor: If the successor status is uncertain (0.5), the agents will randomly decide whether they have a successor (1) or not (0) when they reach 45 years of age.
- Succession: If agents reach 65 years of age and have a successor (1), the age is set to 20 and the successor status is randomly assigned (0/0.5/1).
- Sell farm: If the agents reach 65 years of age and do not have a successor (0), a new farmer will buy the farm. Agent variables are assigned according to the initialisation setup of an agent.

2.10 Observation

What data are collected from the ABM for testing, understanding and analysing it, and how and when are they collected?

Agent characteristics (step=1): Farmer ID, Position, WALRUS model parameters (c_W, c_V, c_G, c_Q, $d_{G,0}$, c_D, a_S, st, c_S), Elevation, Neighbourhood radius, Successor status, Drought threshold, Wet threshold, Transmissivity (kD).

Daily data collector (every step): Farmer ID, Date, Groundwater level, Surface water level, Relative surface water level, $h_{S,min}$, Discharge

Yearly data collector (date = 31/12): Farmer ID, Position, Date, Year of weir installed, Year of channel depth reduced, Threat appraisal, Coping appraisal for weirs, Coping appraisal for reduced channels, Intention to adapt for weirs, Intention to adapt for reduced channels, Weir operation strategy, Days with drought damage, Days with wet damage, Mean days with drought damage.

What key results, outputs or characteristics of the model are emerging from the individuals

1) Number of agents with one and two adaptation measures, based on experiences and learning abilities of the agents;
2) Spillover effect of groundwater levels from agents with adaptation measures to their neighbours;
3) Impact of the spillover effect on the adaptation intention of neighbouring agents.

3. Details

3.1 Implementation

How has the model been implemented? And is the model accessible, and if so where?

The model is coded in Python (version 3.11) and uses the MESA package (version 3.1.4) to structure the agent-based model. The model is accessible in Open Science Framework (10.17605/OSF.IO/PKTVQ) and GitHub (https://github.com/Lars-de-Graaff/upwas-abm)

3.2 Initialisation

What is the initial state of the model world, i.e. at time t=0 of a simulation run?

400 agents are initialised in a grid of 20 x 20 cells, and each grid cell contains one agent. The agents are randomly assigned to the 400 cells. Each grid cell has an elevation value, which is assigned according to a fixed DEM file, as present in Figure 5. Furthermore, Table 2 shows an overview of the initialisation of state variables. The initial fraction of agents that installed measures is dependent on the scenario run (Table 3).

24.4	22.2	21.6	23.4	24.1	24.6	23.0	23.1	26.4	26.1	25.3	24.4	26.7	25.8	27.5	26.1	27.1	29.3	29.1	28.7
21.1	23.2	21.2	22.5	22.1	23.7	24.8	24.7	25.8	26.0	24.3	24.8	26.8	27.0	25.3	27.1	25.8	26.7	28.7	29.4
24.2	21.6	22.3	24.5	23.0	22.3	24.4	25.1	24.8	25.9	24.9	25.9	24.3	26.8	26.4	26.5	27.6	29.3	29.4	28.8
20.1	21.1	24.7	24.2	23.8	22.4	23.5	26.5	23.6	25.5	26.0	26.9	26.0	26.0	26.0	27.8	27.6	26.7	27.0	30.8
21.9	21.9	22.1	22.6	23.8	23.2	23.3	23.1	25.6	24.6	26.8	24.2	26.8	27.2	27.9	26.2	29.1	26.6	29.9	29.3
24.0	22.8	22.0	22.9	22.7	24.1	23.5	23.6	23.2	25.1	25.7	25.8	25.9	26.6	26.8	26.1	28.6	27.5	28.4	29.3
21.9	22.8	23.1	24.2	24.5	24.8	22.2	26.8	26.2	26.4	25.4	24.9	26.5	26.8	26.3	25.1	28.7	28.6	28.9	28.6
24.7	22.9	21.1	23.5	22.3	23.6	22.0	24.3	27.0	24.2	24.1	26.9	26.2	26.4	26.5	26.6	26.9	28.4	29.9	28.7
22.8	23.0	22.6	23.3	24.3	24.6	24.4	24.0	26.7	23.1	26.4	24.4	24.5	27.2	26.9	25.2	26.8	29.1	27.4	30.5
24.5	21.6	22.4	22.6	24.1	22.7	23.3	23.2	26.9	26.6	24.6	25.2	26.7	25.4	27.0	27.2	28.9	29.4	27.9	30.8
21.4	22.5	22.9	24.9	22.2	24.3	24.4	23.2	26.6	23.7	25.6	24.7	25.2	27.9	25.9	27.6	27.9	27.2	27.7	30.3
21.5	23.4	23.6	21.1	24.2	24.5	23.2	25.7	23.9	24.2	24.8	25.8	25.1	27.9	25.9	25.7	26.6	26.6	29.5	30.9
23.8	22.7	22.4	22.6	24.7	23.1	22.7	23.3	23.1	24.6	24.7	26.7	25.6	25.5	27.7	27.5	28.3	29.6	27.1	29.4
20.4	21.2	24.5	23.5	24.9	23.5	22.4	24.3	26.3	27.0	24.4	24.0	26.0	25.7	27.5	27.3	27.8	29.0	28.9	27.6
24.2	21.7	21.6	22.4	24.3	24.6	24.3	23.9	24.0	26.8	26.6	25.2	25.8	27.1	25.2	26.5	25.6	25.8	29.5	28.6
22.8	24.9	23.9	24.6	23.3	24.1	23.5	24.1	24.7	23.7	25.3	26.9	24.4	26.3	25.3	29.3	25.4	26.1	28.1	27.5
22.0	24.7	24.6	21.9	22.9	23.6	23.7	25.7	25.2	26.7	27.0	25.5	26.7	26.6	27.2	26.8	26.0	27.3	27.8	28.9
21.0	22.2	24.6	22.9	22.6	22.5	24.9	24.9	23.9	26.7	26.0	24.4	24.2	27.5	25.8	28.7	26.5	27.3	27.3	27.1
20.3	24.6	23.2	24.7	22.5	23.9	24.9	23.1	23.9	24.5	26.6	26.0	24.9	25.5	27.0	28.5	25.2	26.7	27.4	29.3
23.0	23.8	24.6	22.9	23.2	22.3	23.8	24.0	25.6	25.5	25.7	26.9	26.0	25.5	27.7	27.5	27.1	25.8	27.1	27.7

Figure 5. DEM for 20x20 cells. Values are in meters above sea level.

Is initialisation always the same, or is it allowed to vary among simulations?

The initial fraction of agents who installed the measures and the climate input file depends on the scenario run (Table 4). The rest is initialised as above for all scenarios.

Are initial values chosen arbitrarily or based on data?

The components of protection motivation theory are based on empirical data reported in De Graaff et al. (2025). Informal meetings with experts from the water authority and farmers are used to understand the local context and determine drought and wet thresholds. WALRUS parameters are based on the *Hupsel Brook* catchment (Brauer et al. 2014).

Table 2: Overview of initialisation

Agent		
State variable	**Value/ range**	**Source**
Age	45 ±14	(De Graaff et al., 2025)
Successor	0/0.5/ 1	(De Graaff et al., 2025)
Drought threshold	1900 - 2100	Expert knowledge/ field observations
Wet threshold	400 - 700	Expert knowledge/ field observations
Mean drought stress	10-40	
Neighbourhood radius	1 - 4	
Perceived effectiveness weir	0.3 – 0.7	(De Graaff et al., 2025)
Perceived effectiveness channel	0.3 – 0.7	(De Graaff et al., 2025)
Knowledge	0 – 0.2	Expert knowledge/ field observations
Threat appraisal	0.3 – 0.7	(De Graaff et al., 2025)
Initial weirs installed	See Table 4	(Waterschap Rijn & IJssel, 2024)
Initial weirs + channel reduced	See Table 4	(Waterschap Rijn & IJssel, 2024)

Hydrology		
State variable	**Value/ range**	**Source**
Channel depth (c_D)	1200-2200	Expert knowledge/ field observations
Bankfull discharge (c_S)	c_D/300	
Groundwater reservoir constant (c_G)	15e6 - 20e6	(Brauer et al. 2014)
Quickflow reservoir constant (c_Q)	10 - 15	(Brauer et al. 2014)
Wetness index parameter (c_W)	175 - 225	(Brauer et al. 2014)
Surface water area fraction (a_S)	0.1	(Brauer et al. 2014)
Groundwater reservoir fraction (a_G)	1 - a_S	(Brauer et al. 2014)
Soil type (st)	'Loamy sand'	(Brauer et al. 2014)
vadose zone relaxation time (c_V)	10	(Brauer et al. 2014)
Transmissivity (kD)	0.5×10^3 - 1.5×10^3	

Table 3: Overview of scenarios

	Climate input data	*Only weirs installed*	*Weirs & channel depth reduced*	*Total adapted fraction*	*Adaptative behaviour*
Model performance					
Validation	Observed 2010-2024	0.75 %	0.25 %	1%	Enabled
No adaptation scenarios					
CurClim-NoAdapt	Observed 2010-2024	0 %	0 %	0%	Disabled
DryClim-NoAdapt	KNMI '23 high emission dry 2050 (2050_Hd)	0 %	0 %	0%	Disabled
WetClim-NoAdapt	KNMI '23 high emission wet 2050 (2050_Hn)	0 %	0 %	0%	Disabled
Fixed adaptation scenarios					
CurClim-FixAdaptWeir	Observed 2010-2024	50 %	0 %	50%	Disabled
CurClim-FixAdaptChan	Observed 2010-2024	0 %	50 % (No weirs)	50%	Disabled
Dynamic adaptation scenarios					
CurClim-DynAdapt	Observed 2010-2024	18.7 %	6.3 %	25%	Enabled
DryClim-DynAdapt	KNMI '23 high emission dry 2050 (2050_Hd)	18.7 %	6.3 %	25%	Enabled
WetClim-DynAdapt	KNMI '23 high emission wet 2050 (2050_Hn)	18.7 %	6.3 %	25%	Enabled

3.3 Input data

Does the model use input from external sources such as data files or other models to represent processes that change over time?

The model uses climate data as input for hydrological simulations. Three climate input files are used, depending on the model scenario.

- **Current climate***:* Daily precipitation and potential evaporation data from the KNMI Hupsel weather station (station number 668) was extracted from the KNMI Data Platform (https://dataplatform.knmi.nl/). These data were used to represent the current climate conditions of the study area for the years 2010-2024. This dataset contains four extremely dry years (2018-2020, 2022) and one extremely wet year (2024).
- **Future future**: Precipitation and potential evapotranspiration data from two future climate projections were used from the KNMI '23 climate scenarios (van Dorland et al., 2024). We selected from the High Emission (H) scenarios the Wet (n) and Dry (d) scenarios for the period 2050 (2050_Hn and 2050_Hd). Both scenarios show a decrease in average summer precipitation (2050_Hn = -12%, 2050_Hd = -29%) and an increase in winter precipitation (2050_Hn = +24%, 2050_Hd = +14%). The annual precipitation increases for 2050_Hn with 3% on average, while in 2050_Hd the annual precipitation decreases with 2%. From the 8 available model runs of each scenario, we selected the first run (ens1) and extracted the years 2050-2064 for the model scenarios (Section 2.4).

3.4 Submodels

What, in detail, are the sub-models that represent the processes listed in 'Process overview and scheduling'?

The agents' processes, based on protection motivation theory, are described in detail in Section 2.1.2. This section describes the submodels "update hydrological state variables" and " exchange groundwater".

The water system is simulated with the lumped hydrological model WALRUS, which represent rainfall-runoff processes characterising lowland catchments (Brauer, Teuling, et al., 2014). These include: (1) groundwater–unsaturated zone coupling, (2) wetness-dependent flow routes, (3) groundwater–surface water feedbacks, and (4) seepage and surface water supply (Brauer, Teuling, et al., 2014). Groundwater exchange between grid cells is incorporated to create a spatially-connected groundwater system.

In the ABM, each agent is directly coupled to its own WALRUS model to simulate hydrological processes on the farm scale. The WALRUS parameter values differ slightly between grid cells, to account for spatial differences between the fields. The values are randomly selected from a range around the values used for the *Hupsel Brook* catchment by Brauer et al. (2014b). The hydrological processes operate on a daily time step, with a one-year warm-up period applied during initialisation.

1) Update hydrological state variables

The WALRUS model consists of three reservoirs: soil, surface water, and quickflow (Figure 2). The model uses precipitation (P) and potential evaporation (ET_{pot}) as input variables. Precipitation is first separated between the direct fraction to surface water (P_S) and the fraction received by the land surface (P_V + P_Q). Once this fraction of precipitation reaches the soil, the soil dryness (storage deficit, d_V) determines the fraction that infiltrates in the soil and slowly percolates to the groundwater table (P_V) and the fraction that is led into the quickflow reservoir as runoff or drainage systems (P_Q). The quickflow reservoir releases the water to the surface water reservoir (f_{QS}). Part of the water in the soil evaporates (ET_V), depending on the soil wetness, which determines the evaporation reduction factor (β). Water flowing into or out of the soil reservoir changes the storage deficit (d_V) and the groundwater depth (d_G) responds to this. The surface water reservoir and groundwater reservoir can interact with each other to exchange water in both directions (f_{GS}). The depth of the channel bottom with respect to the land surface is given by c_D. Both groundwater and surface water can receive water from external sources (f_{XG} and f_{XS}). Discharge (Q) is computed from the surface water level (h_S) using a stage-discharge relation. This stage-discharge relation may include a threshold representing a weir ($h_{S,min}$) - if the water level drops below this value, no discharge occurs. A more detailed description of WALRUS can be found in Brauer et al. (2014a).

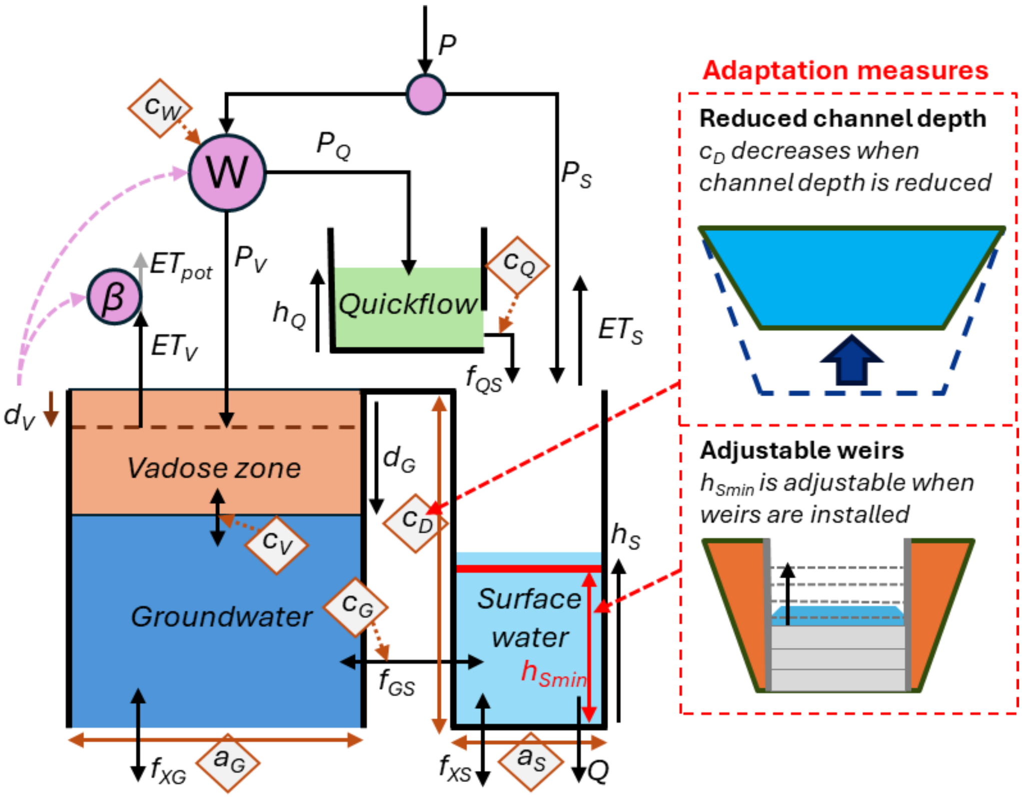

Figure 4. Overview of the WALRUS hydrological model, adapted from Brauer et al. (2014a). Agents can implement an adjustable weir, which allows the agent to alter the surface water level ($h_{S,min}$), and an agent can reduce the channel depth (c_D).

2) <u>Exchange groundwater</u>

Grid cells can only exchange groundwater to neighbouring grid cells (Von Neumann neighbourhood) that have a relatively lower groundwater level than they have. The groundwater flow (f_{XG}) between grid cells is calculated with:

$$f_{XG} = kD * \frac{(el_n - d_{G,n}) - (el_o - d_{G,o})}{l}$$

The calculation is based on the soil's transmissivity (*kD*), the grid cell length (*l*), and the difference between the elevation of the groundwater table of the neighbouring cell (the difference between the elevation of the land surface with respect to sea level, el_n, and the groundwater depth below land surface, $d_{G,n}$) and the agent's own cell ($d_{G,o}$, el_o). The resulting groundwater discharge is added as an inflow flux (f_{XG}) to the neighbouring cell and subtracted from the agent's own f_{XG}. After all cells exchange fluxes, the net inflow or outflow flux is calculated for each cell. This value is then used as an additional inflow or outflow in the subsequent time step to update the hydrological states.

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