A Decision Support Tool for equitable and sustainable water management in the Koue Bokkeveld

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Rodney Tholanah

Makhanda, South Africa

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Declaration of Authorship

I, Rodney Tholanah, declare that A Decision Support Tool for Equitable and Sustainable Water Management in the Koue Bokkeveld is my own work and that it has not been submitted, in whole or in part, for any degree in any other University. I have indicated by reference and acknowledgment the areas that are not my own work.

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Abstract

Water is an important natural resource with multiple domestic and industrial uses. South Africa has a water scarcity problem, with domestic and industrial demand projected to increase due to population growth. One affected area is the Koue Bokkeveld (KBV), an agricultural catchment in the Western Cape. Water scarcity, especially in the summer, can cause conflicts among the farmers. This study sought to determine the extent to which Agent-Based (AB) modelling could be used to model the KBV catchment area and simulate future climate and usage scenarios. The study used the ComMod methodology as it allows stakeholders to be involved at each step of the modelling process, thus improving the model's credibility as a decision-support tool (DST). The model was implemented using Cormas, an Agent-Based Model (ABM) implementation framework built with the Smalltalk language. The model was verified and validated through consultations with the catchment coordinator and through workshops with stakeholders. The ABM reflected the catchment characteristics. Farms known to have water shortages had water shortages in the ABM. However, there was one that did not have shortages, which is attributed to land use change. The ABM was used to run multiple simulation scenarios, and it provides simulation results at the crop field, farm and catchment levels, which allows the ABM to be used as a bottom-up DST.

ACM Computing Classification System

Thesis classification under the ACM Computing Classification System[1] (2012 version valid through 2024):

- **Computing methodologies** ∼ **Agent / discrete models**
- **Computing methodologies** ∼ **Modeling methodologies**
- **Applied computing** ∼ **Agriculture**
- *Applied computing* ∼ *Model verification and validation*

General-Terms: Agent-Based Modelling, Companion modelling, Social-Ecological System, Water Management.

[1] https://www.acm.org/publications/class-2024

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Glossary

AB	Agent-Based
ABM	Agent-Based Model
ARDI	Actors, Resources, Dynamics, Interactions
BI	Bayesian Inference
CA	Cellular Automata
ComMod	Companion Modelling
CORDEX	Coordinated Regional Downscaling Experiment
Cormas	COmmon-pool Resources and Multi-Agent Simulation
DEM	Digital Elevation Model
DST	Decision Support Tool
ET_0	Reference Crop Evapotranspiration
EWR	Environmental Water Requirements
FAO	Food and Agriculture Organization
GCM	Global Climatic Model
GIS	Geographic Information System
HRU	Hydrological Response Unit
IPCC	Intergovernmental Panel on Climate Change
K_c	Crop Coefficient
KBV	Koue Bokkeveld
LULC	Land Use Land Cover
MAS	Multi-Agent System
NSE	Nash-Sutcliffe Efficiency
ODD	Overview, Design Concepts, Details
ODD+D	Overview, Design Concepts, Details and Human Decision Making
R^2	Coefficient of Determination
RCA4	Regional Climatic Atmospheric Model version 4
RCP	Representative Concentration Pathway

RPG	Role-Playing Game
RW	RiverWare
SES	Social-Ecological System
STREAM	STandardised REserve Analysis and Monitoring tool
SWAT	Soil and Water Assessment Tool
TPB	Theory of Planned Behaviour
UML	Unified Modeling Language
VIC	Variable Infiltration Capacity
WRC	Water Research Commission
WUA	Water Users Association

1

Introduction

1.1 Context of research

Water is an essential natural resource with multiple industrial and domestic uses. South Africa has a water scarcity problem, and demand for industrial and domestic water use will increase due to population growth, thus exacerbating the problem (Crookes *et al.*, 2018, Kidd, 2016). In 1998, the South African government promulgated the South African National Water Act (Act 36 of 1998), which provides guidelines on the equitable sharing of water resources. It stipulates measures to protect aquatic ecosystems (Schreiner, 2013). Environmental Water Requirements (EWR), which specify the minimum water required in river systems to be functional and sustainable, are also covered in the Act. However, these objectives are not being met, given the water scarcity problem. Competition for limited water resources also results in conflicts, and little consideration is given to the EWR. One of the regions in South Africa affected by water scarcity is the Koue Bokkeveld (KBV) region, an agricultural area located in the southwestern part of South Africa in the Western Cape.

The KBV has multiple mountain ranges that form part of the Cape Fold Belt (Booth, 2009). According to Vos (2014), the landscape in the region varies sharply, with a marked difference between the highest and lowest points.

Rainfall in the KBV region varies. The southwestern part of the catchment has higher rainfall (more than 1000 mm per year) compared to the eastern part, which gets less than 400 mm per year (Vos, 2014). The KBV region has a Mediterranean climate, meaning it receives most of its rainfall in winter (Midgley *et al.*, 2005).

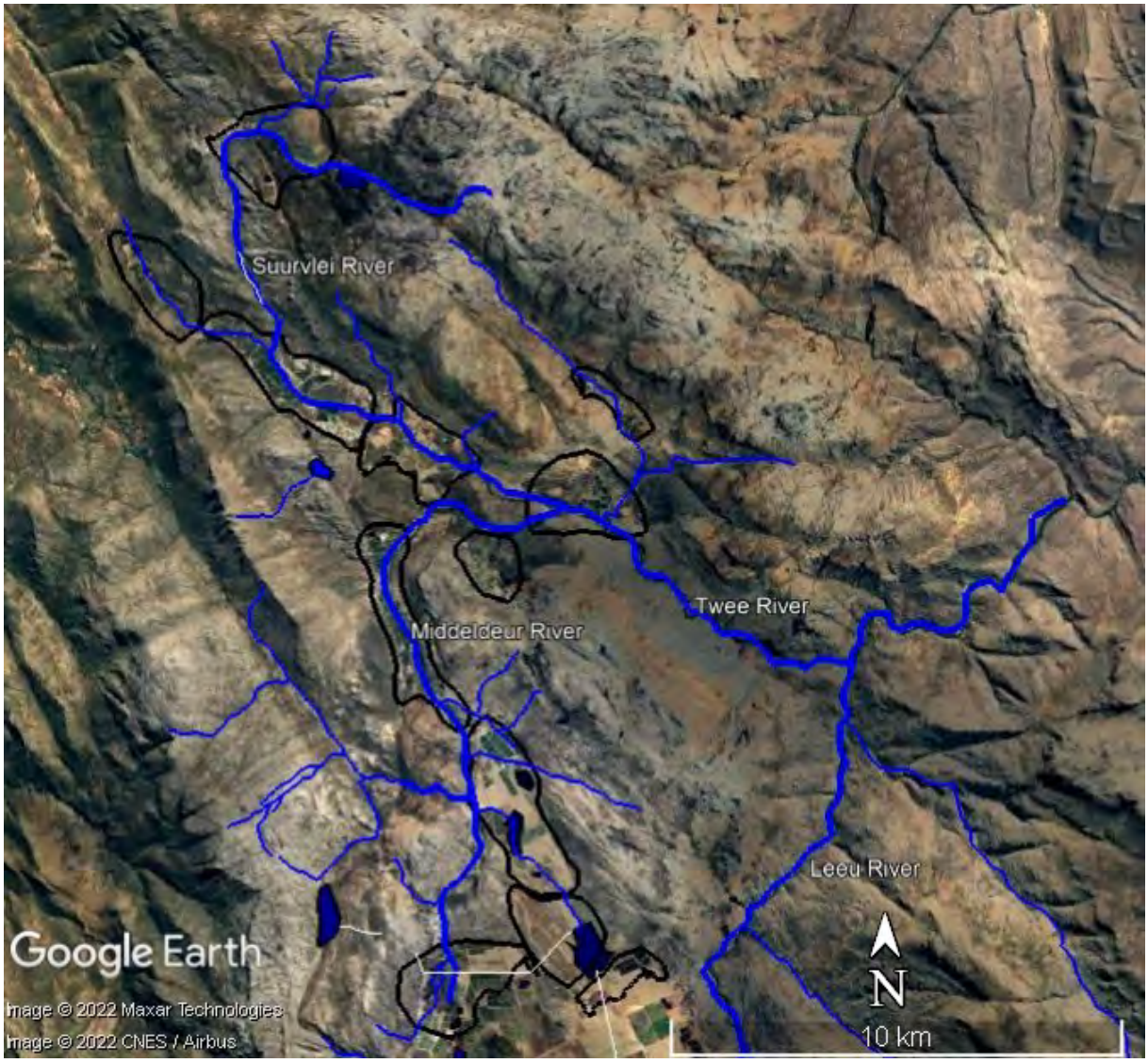

Figure 1.1: Relief map of part of the Koue Bokkeveld catchment (quaternary catchment E21H), which is located in the Olifants-Doring catchment and farm boundaries (Google Earth 7.3, 2022)

In summer, the KBV has high temperatures with low temperatures during winter. According to Vos (2014), the temperature varies similarly to the variation in topology. In summer, the temperature rarely exceeds 32°C; in winter, the minimum temperature is nearly zero.

As shown in Figure 1.1, the Twee, Middledeur and Suurvlei are the main rivers in the KBV catchment. The Suurvlei River flows from the north towards the southeast, while the Middledeur River (which has the Hex River as one of its tributaries) flows from the south to the northeast. The two rivers join and become part of the Twee River.

1.2 Problem statement

Water scarcity has increased competition amongst users, straining the river systems. Computer modelling could be used to find solutions to the sustainable sharing of the limited water resources among the KBV stakeholders. This project used agent-based (AB) modelling to co-develop a Decision Support Tool (DST) with KBV stakeholders that could assist in the development of an effective water management strategy to use the limited water resources sustainably at a later stage. The project aims to model the current situation and simulate future scenarios based on climate variability projection and other potential changes.

1.3 Research question

To what extent can AB modelling be useful in modelling the KBV catchment area and simulating climate/usage scenarios?

1.4 Research objectives

The objectives of this research were to:

- Develop a generalisable and realistic ABM for the KBV region through collaboration with the farmers and other stakeholders in the KBV region.
- Provide a DST that could assist in developing a water management plan at a later stage.
- Investigate how climate variability affects water availability and provide relevant information to enable the creation of strategies for use by farmers in combating the problem.

1.5 Approach

AB modelling in socio-ecological systems (SESs) is an iterative process involving multiple stakeholders (Schlüter *et al.*, 2021). This study used Companion Modelling (ComMod), which is an

iterative and participatory approach that allows for building ABMs with stakeholders to discuss natural resource sharing (Barreteau *et al.*, 2003).

Three stakeholder workshops were organised. The *Actors*, *Resources*, *Dynamics* and *Interactions* (ARDI) method was used in the first workshop to obtain more information about the catchment. ARDI is a technique used in ComMod to understand the various entities and processes in a system by discussing with stakeholders.

A conceptual model was developed using the information obtained from the first workshop and presented to the stakeholders for feedback. A survey was also conducted to obtain information regarding the stakeholders' strategic farming decisions.

The ABM was implemented using the Common-pool Resources and Multi-Agent System (Cormas) simulation environment (Bousquet *et al.*, 1998). The ABM was loosely coupled with the Soil and Water Assessment Tool (SWAT) hydrological model. The model and its results were presented to stakeholders in the third workshop.

1.6 Limitations

- Some stakeholders did not respond to the survey; hence, some of the data used in the ABM was estimated using Geographic Information Systems (GIS) data or was provided by researchers working in the catchment.
- The stakeholders did not provide information about their water use licences; therefore, water use licenses do not affect model execution. However, the ABM has the facilities to include water use licenses.
- The ABM does not include any groundwater due to a lack of information.
- Water losses from dams through evaporation and seepage were not included due to insufficient data.

1.7 Thesis outline

The remainder of this thesis is arranged as follows:

Chapter 2: *Hydrological Concepts and Models*: Describes hydrological concepts and models. It discusses studies that used hydrological models and irrigation concepts.

Chapter 3: *Concepts and Technologies for Computer Modelling*: An overview of modellinga and AB modelling. The concepts and data used in related studies are also discussed and explained.

Chapter 4: *Methodology and Model Design*: This chapter presents and discusses the data collection and stakeholder workshops that were carried out. It also describes the conceptual model of the ABM.

Chapter 5: *Implementation, Verification and Validation*: This chapter presents the implementation details of the ABM. It also describes the verification and validation that was performed.

Chapter 6: *Results and Discussion*: The chapter explains the simulated scenarios and their results.

Chapters 7: *Conclusion and Future Work*: This chapter concludes the thesis, highlights the contributions of the research and provides directions for future work.

2

Hydrological Concepts and Models

This chapter describes catchment concepts, including the hydrological cycle and studies that used hydrological models to model catchments.

2.1 Hydrologic cycle

According to Brooks (2012), catchments (watersheds or drainage basins) are regions where water enters as precipitation and leaves the system at a single point. The water flows in a river system composed of a stream network, and the tributaries join the main channel, allowing water to leave the system and enter another catchment or a lake. Many decisions about the management of water resources are made at the catchment level.

The hydrologic cycle refers to processes that happen to water as it moves between different states and storages (Brooks, 2012). In catchments, this process is responsible for the movement of water.

Figure 2.1 shows the main components and processes of the hydrologic cycle. According to Zhang *et al.* (2002), the sun provides the energy needed to power the hydrologic cycle. The energy from the sun causes water from oceans and other water bodies such as lakes to evaporate. Plants transpire, thereby losing water to the atmosphere. The evaporated water and water from transpiration (collectively known as evapotranspiration) condenses to form clouds, which cause precipitation in the form of rain or snow in different parts of the catchment.

Some precipitation permeates the soil (the unsaturated zone region) through infiltration, thus increasing soil moisture (Zhang *et al.*, 2002). Rainwater that does not infiltrate becomes part

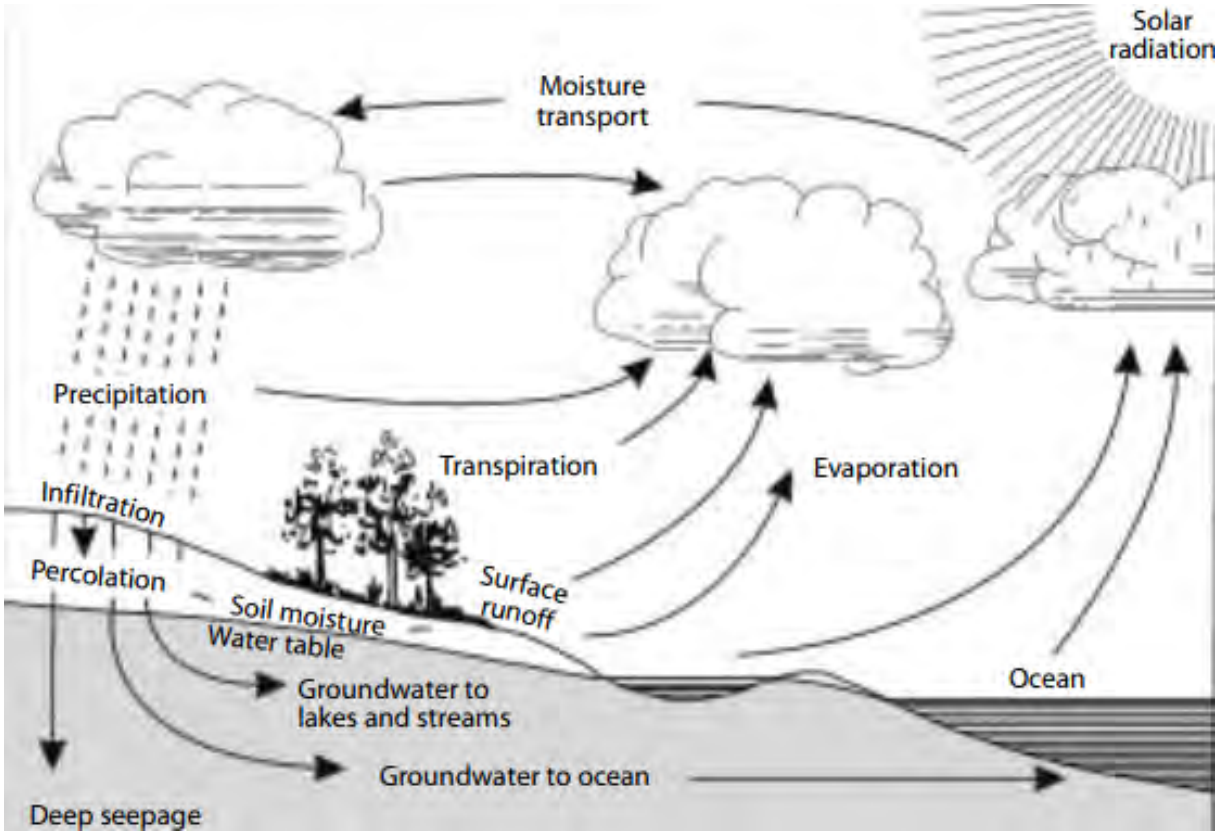

Figure 2.1: The hydrologic cycle – taken from Zhang *et al.* (2002)

of the surface runoff, which returns to streams and rivers. Some of the water that infiltrates becomes interflow, which moves towards lakes and streams following a path underneath the soil but above the water table, while the rest of the water goes through the process of percolation, whereby the water recharges the groundwater under the water table called the saturated zone. The water in the saturated zone also flows towards the ocean and can contribute to streamflow.

One of the key concepts of the hydrologic cycle is the water balance. For a given region, the water volume change in a catchment is the difference between water that enters the catchment and water that leaves the catchment (Zhang *et al.*, 2002). According to Zhang *et al.* (1999), the water balance of a catchment can be represented as:

$$P = ET + R + D + \Delta S \tag{2.1}$$

where P is precipitation, ET is evapotranspiration, R is runoff, D is groundwater recharge, and ΔS is the change in water stored in the soil.

2.2 Rivers

Rain collects and forms multiple streams, which feed larger streams called river channels. Although some precipitation falls directly in the river, the amount of rain that directly contributes to a river's water is negligible compared to the amount of water from the tributary streams due to the small surface area of rivers (Bukaveckas, 2009).

There are multiple types of rivers, namely perennial, intermittent and ephemeral. Perennial rivers flow throughout the year, intermittent or seasonal rivers only flow during the wet season, while ephemeral rivers only flow after precipitation has occurred (Brooks, 2012).

According to Brooks (2012), a river's water flow (usually measured in m^3/s) can be divided into baseflow and direct runoff. Baseflow is groundwater that flows into perennial rivers (Brooks, 2012, Levy and Xu, 2011), while direct runoff is the combination of interflow, surface runoff and rainfall that falls directly into the river and nearby areas, called channel interception.

2.3 Modelling catchments

Many hydrologic simulation models have been developed mainly to predict the runoff from a catchment given precipitation data. According to Brooks (2012), hydrologic models can be categorized according to the way the models represent space and how the models are structured. Hydrologic models can be spatially distributed, meaning the models represent the heterogeneity of a region or the models can be lumped, meaning they do not consider the heterogeneity of a region. Regarding structure, models can be physically based, meaning that they explicitly model the hydrological processes, whilst empirical hydrological models do not model the hydrological processes. Physically-based hydrological models are process-based, while empirical hydrological models are mathematical models as described in Section 3.1.1. Examples of hydrological models are SWAT, RiverWare and Pitman models.

2.3.1 SWAT

The Soil and Water Assessment Tool (SWAT) is a hydrological model that was developed by USDA-Agricultural Research Service (ARS) and is maintained and updated by the SWAT devel-

opment team (Arnold *et al.*, 2012). It was developed to assess land use and management change impacts on water quality and quantity in catchments.

The SWAT model is a semi-distributed and physically based hydrological model. The model represents various parts of the hydrologic cycle, including precipitation, evapotranspiration, infiltration and percolation. SWAT divides a catchment into sub-catchments, and the model further divides the sub-catchment into different hydrological response units (HRUs). The HRUs usually consist of areas with common characteristics, such as the same land use and soil type (Arnold *et al.*, 2012).

2.3.2 RiverWare

RiverWare (RW) is a model that models river and reservoir systems, allowing management authorities to analyse water resources in river systems and reservoirs and make management decisions (Zagona *et al.*, 2001).

Unlike the SWAT model, RiverWare uses object-oriented programming extensively (Zagona *et al.*, 2001). Although the model has a graphical user interface, it provides objects representing a catchment's components, including reservoirs, canals, and river reaches. Each object contains *slots*, which can store time series data or simpler data used by the objects during simulation. To set up the model, a modeller can represent a catchment using the available objects and link them together to form a river-reservoir network. The modeller can then manually provide data for the slots or use external files.

A user of the model can also add operation rules to the model setup (Zagona *et al.*, 2001), which can specify when various processes can happen. For instance, if a particular reservoir's volume exceeds a certain threshold, its water would be released as a form of flood control. Unlike the SWAT model, which operates at a daily timestep, the RiverWare model can operate at any timestep.

2.3.3 Pitman

The Pitman model was developed by Pitman (1973) to simulate streamflow data that can be used for water resources management. Unlike the SWAT and RiverWare models, the original Pitman

model used a monthly timestep and was lumped, meaning it did not represent the heterogeneity of catchments.

According to Hughes (2013), newer versions of the Pitman model are semi-distributed and use daily timesteps to reduce uncertainty. Unlike the SWAT model, which is physically based, the Pitman model is a conceptual or empirically based hydrologic model, which means that the Pitman model simplifies the representation of the hydrological processes. Like the SWAT model, the Pitman model divides the catchment into sub-catchments.

2.3.4 Variable Infiltration Capacity model

The Variable Infiltration Capacity (VIC) model is a hydrologic model developed to model macroscale hydrology (Liang *et al.*, 1994). Like the Pitman and SWAT hydrologic models, the VIC model is semi-distributed. The VIC model represents soil using the upper and lower layers of soil. Different land cover types represent vegetation, and the vegetation's roots can reach either layer one or layer two, depending on the vegetation soil types. The upper layer responds faster to precipitation compared to the lower layer.

According to Liang *et al.* (1994), during each timestep (hourly or daily), the model calculates the water that moves from upper to lower layers of each landcover type, in addition to water that flows as surface runoff and water that flows laterally in the upper layer as subsurface runoff.

Various researchers have improved the VIC model, including modifying the model to be coupled more efficiently with other models and allowing the model to be run in parallel, thus utilising more computational power (Hamman *et al.*, 2018).

2.4 Studies using hydrological models

Hydrologic models have been used in numerous studies ranging from predicting water availability under different climate projections (Gumbo and Kapangaziwiri, 2021) and climate and usage projections (Bennett *et al.*, 2019) to investigating groundwater recharge (Gyamfi *et al.*, 2017).

According to Guug *et al.* (2020), predicting the amount of water in a region is necessary to manage water resources sustainably. The authors used the SWAT model to make predictions

of water availability in the Sherigu catchment in Ghana. The researchers used input data, including precipitation, temperature, and relative humidity, obtained from two weather stations in the catchment to set up the model. The study also used soil data, a Digital Elevation Model (DEM) of 30m x 30m, and Land Use Land Cover (LULC) data that had a resolution of 250m. The DEM defined various physical features, such as streams and slopes.

The results showed that 72% of precipitation was lost through evapotranspiration annually, 14% to runoff, and another 14% to soil and groundwater storage. According to the authors, the results suggested that the groundwater table was close to the surface; therefore, building percolation tanks would be helpful (Guug *et al.*, 2020). In addition, dams could be made to store surface runoff, which significantly contributes to the discharge.

Hughes (2004) identified a critical need for an integrated modelling tool that effectively combines surface water and groundwater dynamics, particularly in southern Africa. The region faces challenges related to data scarcity and the urgent need for regional water resource assessments. Understanding the interactions between groundwater and surface water is essential for sustainable water resource management, especially as reliance on groundwater increases in arid areas.

The Pitman model was used in the study due to the model's wide usage in Southern Africa, simplicity and flexibility (Hughes, 2004). Groundwater recharge and discharge were incorporated into the model and were based on established groundwater flow principles and utilised well-understood hydrological parameters. To evaluate the effectiveness of the new components, the modified Pitman model was used to model the Buffelspruit River catchment in South Africa and the Cuito River catchment in Angola. Each catchment has different baseflow characteristics, making them ideal for testing the model. The model's performance was assessed through comparisons with existing hydrological data.

The results of the modified Pitman model, which incorporated groundwater recharge and discharge functions, indicated a small but significant improvement in simulating the groundwater baseflow component of total runoff compared to the original model (Hughes, 2004). The study's author cautioned that there is a need for further testing and refinement to ensure the model would be suitable for use in other types of catchments.

According to Gumbo and Kapangaziwiri (2021), many areas in southern Africa will suffer from a lack of water due to increased population, urbanisation and climate change. Climate change

will reduce precipitation in the region. To explore the effects of climate change scenarios on the streamflow of the Pungwe River, which is one of the primary water sources for Mutare, a city in Zimbabwe, the authors set up a Pitman model. The model results provide data for decision-making by the water management authorities.

Some of the reasons Gumbo and Kapangaziwiri (2021) used the Pitman model instead of other models, such as SWAT, were that the model required less data than other hydrological models and other researchers had used the model in similar studies. Various data inputs were used to configure the model, including historical precipitation data from 1960 to 2017 and ten Global Climatic Models (GCMs) using Representative Concentration Pathways (RCP) 4.5 and 8.5. The RCP values measured carbon emissions, with 4.5 being the lowest and 8.5 being the highest emission scenario. The Intergovernmental Panel on Climate Change (IPCC) defines RCP 4.5 as a carbon emission scenario where carbon emissions peak in 2040, while RCP 8.5 is a scenario where carbon emissions peak in 2100 (Pachauri *et al.*, 2014).

Results for the RCP 4.5 scenario showed that there would be an increase in streamflow of 2.48 % from 2020 to 2060 and 1.48% from 2061 to 2099, while the RCP 8.5 scenario showed a streamflow decrease of -7.83% from 2020 to 2060 and -9.73% from 2061 to 2099. These results suggest that if carbon emissions remained at the same level, the city of Mutare would face acute water shortages; therefore, the water management authorities needed to develop strategies to lessen the impact of the decrease in streamflow.

Similar to Gumbo and Kapangaziwiri (2021), Bennett *et al.* (2019) explored the effect of climate change on water availability and usage changes, such as an increase in water demand. According to the authors, in the USA, the management of water resources was primarily based on historical streamflow data and water demand by society. However, streamflow and water demand are subject to change; hence, there was a need to investigate the effect of changes in streamflow and water demand on agricultural and energy production. The authors chose the San Juan River (SJR), which is one of the major tributaries of the Colorado River Basin, because it was an essential contributor to the USA economy, and the river system was also susceptible to climate change.

Bennett *et al.* (2019) combined the VIC and RiverWare models. The VIC model calculated the streamflow, which was input into the RiverWare model, which simulated the management operations, including inter-basin transfers and water allocations. The authors ran multiple scenarios

for 1970 - 2099, which involved using historical climate data and current water usage, historical climate data and increased water demand, future climate and vegetation with current water usage, and future climate and vegetation and increased water demand. The authors used various metrics in their analysis, including the amount of water in the Navajo Reservoir, instream flows, and SJR flow output into the Colorado River. Unlike Gumbo and Kapangaziwiri (2021), who used ten GCMs and RPC values of 4.5 and 8.5, the authors used six Earth System Models (ESM) and an RCP of 8.5.

The scenario that used future climate predictions and increased water demand showed that all the metrics were affected negatively. However, there was a slight worsening in the metrics compared to the second scenario, which the authors attributed to policy changes due to different precipitation levels. Results of the scenario involving future climate predictions and increased water demand showed that the metrics would be severely affected, and thresholds defined for environmental flows would not be met. The water shortages could affect municipalities, power generation, and the economy. The researchers emphasised the need for flexible operation rules to mitigate the impacts of increased water demand and climate change.

2.5 Comparison of studies using hydrological models

The hydrological studies noted above used different methods to calibrate the hydrologic models, including automatic and manual calibration. Similarly, most authors used different performance measures, including Nash–Sutcliffe efficiency (NSE) and coefficient of determination (R^2), to evaluate their model's calibration results. NSE measures the performance of a model by considering both the mean and variability and ranges from negative infinity to 1, with values closer to 1 indicating better performance compared to values further from 1 (Nash and Sutcliffe, 1970). R^2 measures how much a model fits observed data, and its value ranges from 0 to 1, with values closer to 1 indicating better model performance than those closer to 0 (Di Bucchianico, 2008). The simulation results varied among the studies, with some models performing better than others. For example, Hughes (2004) obtained an R^2 of 0.708 when modelling the Cuito River catchment using the original Pitman model, which improved to 0.743 when using the new Pitman model that incorporated groundwater explicitly.

In exploring the effects of climate change, Bennett *et al.* (2019) used 6 ESMs while Gumbo and

Kapangaziwiri (2021) used 10 GCMs to simulate precipitation and temperature changes under different RCPs. Both authors used statistically downscaled data; however, the latter used RCP 4.5 and 8.5, while the former used RCP 8.5 only.

The hydrological studies used hydrographs, scatter plots, and flow duration curves to represent the model results. Visualisations were similar across the studies, with the authors using plots to demonstrate the relationship between observed and simulated flows. However, each study used visualisations to represent their specific research questions. For instance, Gumbo and Kapangaziwiri (2021) used a hydrograph to show the relationship between monthly observed flows and simulated flows and flow duration curves to visualise water availability. In contrast, Gyamfi *et al.* (2017) used scatter plots to visualise the relationship between simulated and observed flows.

One of the weaknesses in the studies is that human behaviour is not explicitly represented. Bennett *et al.* (2019) used RiverWare to incorporate reservoir operation rules to express human impact in the catchment but remarked that they wanted to include an ABM in their study to make it more accurate. Integrating ABM into these studies would allow them to capture human behaviour's two-way impact on water resources and vice versa.

2.6 Agricultural water usage in the Western Cape

2.6.1 Rainfall

Although the climate in the Western Cape varies, it generally has a Mediterranean climate (Midgley *et al.*, 2005), characterised by dry summers and wet winters. The mean annual rainfall ranges from 3600 mm per year in some areas to as little as 100 mm per year in others. One of the contributing factors to the mean annual rainfall variability is the Western Cape's geography. The Cape Fold Belt allows for orographic rainfall, resulting in a sharp rainfall gradient and some regions in the province receiving more rain than others.

2.6.2 Types of crops cultivated

Since the Western Cape is particularly suitable for cultivating deciduous fruits due to the cold winter temperatures, fruit farming is an important component of agriculture in the province

(Taylor and Gush, 2014). Fruits cultivated in the region include citrus (e.g. lemons and soft citrus), stone fruit (e.g. plums and nectarines) and grapes. Farmers also cultivate vegetable crops such as cabbages and spinach.

2.6.3 Irrigation

Crops need multiple inputs to thrive, including sunshine, water and nutrients from the soil. Due to South Africa being a water-scarce country, farmers supplement crops' water from rainfall through irrigation.

Farmers utilise various irrigation methods. According to Eisenhauer *et al.* (2021b), the main irrigation methods are micro-irrigation, sprinkler irrigation and surface irrigation. The choice of a particular irrigation system depends on multiple factors such as the type of crops being irrigated, installation, usage and maintenance cost and water availability.

Sprinkler irrigation systems range from mobile single sprinkler systems to multiple sprinkler systems, either static (solid-set) or mobile (moved-lateral) (Eisenhauer *et al.*, 2021b). The main differences in these systems are the number of sprinklers and mobility. Single-sprinkler systems utilise one sprinkler to irrigate an area and are moved to cover the site to be irrigated. A drawback of such systems is that they sometimes apply water beyond the area to be irrigated. Solid-set and moved-lateral systems comprise multiple sprinklers connected to a pipe supplying water.

Surface irrigation involves applying water to a field to move uniformly across the field (Eisenhauer *et al.*, 2021b). For this method to be effective, the area being irrigated must have a gentle slope and the portion being irrigated must have a furrow or ditch to prevent water from going to other places. An advantage of this technique is that it is cheaper than the sprinkler method, as surface irrigation requires less pressure. However, usage of this method can result in a runoff problem where water leaves the region being irrigated.

Micro irrigation is similar to sprinkler irrigation in that it uses a network of pipes to supply water but uses micro-sprinklers instead of sprinklers. The micro-sprinklers provide water to a localised area, which could be an individual plant (Eisenhauer *et al.*, 2021b), making it a highly efficient method compared to surface and sprinkler irrigation, and thus invaluable in water-scarce regions.

However, the method is expensive to install, and the micro-sprinklers need to be cleaned often as soil and other materials can easily block the outlet.

2.6.3.1 Water sources for irrigation

There are three water sources for irrigation: groundwater, surface water and reclaimed water (Eisenhauer *et al.*, 2021c). Groundwater is water obtained from underground, e.g., shallow or deep wells and springs. Shallow wells are usually located close to streams and require less powerful pumps than deep wells.

Surface water is obtained from rivers through open canals or pressurised systems (Eisenhauer *et al.*, 2021c). Open canals are used when the fields are far from the river source. One main disadvantage of such systems is that they lose water through seepage, especially early in the rainy season, due to the relatively dry antecedent conditions of the soil. On the other hand, pressurised systems use pipelines to channel water from the river water source to the fields. A drawback of these systems compared to canals is the high installation costs. Pipelines require water to be pumped if the gradient rises; however, gravity can be enough to maintain the water pressure in the pipelines if there is a downward slope.

2.6.3.2 Irrigation scheduling

Eisenhauer *et al.* (2021a) likened the soil to a water reservoir and described irrigation scheduling as the frequency and quantity of water applied to the soil to maintain an optimum moisture level for crop growth. There are multiple irrigation scheduling strategies, each considering various factors. Each technique is based on evapotranspiration, water balance, soil moisture, or plant water status (Gu *et al.*, 2020).

Evapotranspiration and water balance methods (ET-WB) use evapotranspiration ET_c combined with a soil water balance equation when determining the water available to crops in the root zone. A critical process in this type of irrigation scheduling is determining ET_c, which can be measured using instruments such as lysimeters. Since this task is expensive and time-consuming, ET_c is usually estimated (Gu *et al.*, 2020).

Allen *et al.* (1998) developed a method to calculate ET_c through the use of reference crop evapotranspiration (ET_o) and crop coefficients (K_c). ET_o is the amount of water lost to the atmosphere by a grass crop growing under optimum conditions in a given climate. The only factors influencing ET_o are climatic factors such as air temperature and humidity. This means ET_0 varies between different climates and seasons. K_c is the ratio of ET_c to ET_0 and it is calculated through the use of experiments. The formula for calculating ET_c is given by:

$$ET_c = K_c \times ET_0 \tag{2.2}$$

According to Gu *et al.* (2020), one of the advantages of ET-WB methods is that they can still work even when soil data is unavailable, provided that the daily irrigation demand is provided promptly. However, one of their drawbacks is that estimating ET_c for large fields between 10 to 100 hectares is difficult.

Soil moisture (θ) based irrigation schedules use sensors that measure the θ level and turn on irrigation when the moisture drops below a certain threshold (Gu *et al.*, 2020). Neutron sensors measure the θ level. An important aspect of θ-based irrigation schedules is determining the threshold of θ for triggering irrigation. These thresholds are specific to different locations and crops and are therefore determined experimentally.

One of the advantages of θ-based irrigation scheduling techniques is that they allow for precise irrigation in terms of timing and region in the field that needs irrigation (Gu *et al.*, 2020). However, a disadvantage of the method is that the irrigation scheduling will be ineffective if the sensors provide incorrect data (Evett *et al.*, 2011).

Plant-based irrigation scheduling methods involve measuring some physical attributes of a plant to determine whether irrigation should be applied (Gu *et al.*, 2020). Jones (2004) discussed various methods for implementing the scheduling technique, including measuring leaf thickness, stem diameter or sap flow. A vital aspect of this technique is choosing attributes of the plant that are sensitive to shortages of water. Like θ-based methods, plant-based methods do not provide the amount of water to be administered. Instead, irrigation is stopped after the measured attribute reaches a certain threshold.

2.6.3.3 Irrigation prioritisation

Closely related to irrigation scheduling is crop prioritisation. Given water scarcity, farmers must provide water optimally to maximise yield. According to Vedula and Mujumdar (1992), crops have crucial growth/development stages with high water stress sensitivity; thus, farmers must prioritise their most important crops, especially during the critical phases.

When irrigation demand exceeds available water, farmers assign different priorities to their crops, depending on their importance, generally determined by the economic value derived from the crop output (Haro-Monteagudo *et al.*, 2019). Higher-priority crops are supplied with more irrigation water than lower-priority crops.

2.7 Chapter summary

This chapter provided an overview of hydrological concepts, including the hydrologic cycle and catchment dynamics. It also discussed the application of various hydrological models, such as SWAT, RiverWare, Pitman, and VIC, in simulating catchment processes and water management strategies. These models vary in their approaches, from physically-based to empirical and from lumped to semi-distributed, offering diverse tools for understanding and managing water resources. Additionally, studies using these models were described, highlighting their use in predicting water availability, assessing the impact of climate change, and exploring land use and land cover changes on hydrology. The chapter compares the studies, noting differences in calibration methods, model performance metrics, and the importance of integrating human behaviour in future hydrological studies through techniques like AB modelling. The chapter concludes by providing an overview of agricultural water usage in the Western Cape, emphasising irrigation.

3

Concepts and Technologies for Computer Modelling

This chapter introduces the different types of computer models and the literature relevant to this study. AB modelling is explained in depth.

3.1 Introduction to Computer Modelling

A model is an abstract representation of reality (Tolk, 2015). Models simplify systems (Sayama, 2015), which allows a better understanding of the systems. Therefore, modelling is the process of building such representations. The representations are used in simulations where simulation software operates on the model (Maria, 1997).

3.1.1 Types of computer models

Mathematical models use a set of equations to model systems, and there are multiple types of such models, including empirical/statistical, optimisation and structural models (Sargent, 2015). According to Chambers and Hastie (1992), statistical models consist of three parts, namely, the formula, data, and stochastic parts. The formula represents the relationship between the data considered by the model. Data refers to the system data considered in the model, and the stochastic part is the non-deterministic part of the model, which modellers often introduce due to uncertainty.

Optimisation models are used to maximise or minimise an objective function (Olson, 2003). These models also comprise three parts: the decision variables, the objective function, and constraints. Decision variables represent the variables the decision makers can choose to obtain a maximum or a minimum from the objective function. The objective function is a function that describes the relationship between the decision variables (Sargent, 2015).

Structural models describe a system based on relationships between events that occur in a system and the conditions that trigger these events (Sargent, 2015). There are two main categories of structural models: analytic models and discrete-event simulation models. An example of an analytical model is a continuous simulation model, while an example of a structural model is a process-based model. Agent-based models (ABMs), which are a type of process-based models (Müller *et al.*, 2013), are explained in detail in Section 3.2.

3.1.2 Studies using computer models for agricultural yield scenarios

Schlenker and Roberts (2009) developed three statistical models to determine the linkage between temperature and corn, soybean and cotton yields. The authors used detailed weather and crop yield data from 1950 to 2005 from various locations in the USA. The authors discovered a positive correlation between yield and temperature for all the crops. However, this relationship did not hold at certain temperatures for the different crops, and the yields would start decreasing as temperature increased. The researchers ran their model using data from a climate model under different carbon emission scenarios, and they discovered that if the growing locations were fixed, the yield would decrease by 30-46% under the slowest warming scenario and 63-82% under the fastest warming scenario for the period 2020-2099.

Soltani and Sinclair (2011) developed a process-based model called SSM-Chickpea, which allowed farmers to manage chickpea crops to obtain high yields optimally. The researchers identified multiple processes that needed to be represented in the model to model chickpea growth and yield. The processes included chickpea development stages and their duration and leaf area development. In modelling each of these processes, the authors utilised experimentally observed relationships.

The Decision Support System for Agrotechnology Transfer (DSSAT) system is a process-based model that was developed to simulate crop growth, development, and yield based on various input

parameters, such as weather, soil, and management practices, to various agricultural stakeholders, including farmers and policymakers, which they can use for decision making (Jones *et al.*, 2003). DSSAT has been used in multiple studies, such as one described by Hoogenboom *et al.* (2019), in which crop rotation of soybeans and chickpeas for a site in Hyderabad, India. Soybeans are grown during the rainy season, and chickpeas (which require less water than soybeans) are grown afterwards. In the study, 30 simulations were run, and the weather generator component of DSSAT was used to generate weather data due to the lack of input weather data. Each simulation was run for 42 years, and the results showed that soybean yield was constant and ranged from 2.8 t/ha and 3.3 t/ha, while chickpeas ranged from 0 t/ha and 0.4 t/ha. This experiment showed that there is a benefit in using residual soil moisture to cultivate chickpeas after soybeans have been harvested.

The Agricultural Productions Systems sIMulator (APSIM) is a modelling framework that links models for soil, crop, and pasture livestock biophysical processes (Keating *et al.*, 2003). Similar to DSSAT, APSIM is process-based and can be used to improve management strategies and support sustainable agriculture. Chimonyo *et al.* (2016) used APSIM to study sorghum-chickpea intercropping. The study conducted a field experiment in which sorghum and chickpea were cultivated in sub-plots at Ukulinga Research Farm in Kwazulu-Natal, South Africa. The sub-plots were optimally managed, with fertilizer applied for sorghum, the main crop. This was done to calibrate the model and determine the baseline. The biomass results from the simulation were determined to be satisfactory, and it was attributed to the process that the model uses data regarding the level of sunlight available to plants in determining the biomass the plants would accumulate. The researchers discovered that APSIM's yield results deviated by 7% from the observed yield. However, the cowpea yield was overestimated by 31%, which was attributed to the slight overestimation of biomass.

The main difference between the models was the approaches used in each. The statistical model focused on analysing historical crop yield data to identify relationships. The authors used these relationships to make predictions. In contrast, the SSM-Chickpea process-based model relied on experimentally observed processes involved in the growth of chickpea plants. The processes were represented explicitly in the model, which allowed the authors to interpret the SSM-Chickpea model results better than the interpretation provided by Schlenker and Roberts (2009) of their model results. Similarly, DSSAT and APSIM are process-based, and they model various processes involved in plant growth, thus allowing for better interpretation of model results. However, unlike

the SSM-Chickpea model, DSSAT and APSIM models are more flexible and can be adapted to model other crops.

Due to the reliance on historical data by Schlenker and Roberts (2009), the authors had to use a large amount of data when developing the model. In contrast, Soltani and Sinclair (2011) used much less data when developing the SSM-Chickpea model. Instead, the researchers used equations obtained from studies that analysed various aspects of the development of chickpea plants. This is a similar approach to that used in DSSAT and APSIM.

Both studies validated their models. Schlenker and Roberts (2009) selected 48 years randomly from their data and used the data to estimate parameters for their models and other previously developed models. In the next step, the authors used the models to predict the yield for the remaining eight years. The researchers compared the models' results with those of a model that did not consider weather variables. The researchers found that the models they developed reduced the root mean square error (RMSE) by up to 360%. On the other hand, Soltani and Sinclair (2011) validated their model by comparing the model's leaf area index (LAI), mass, nitrogen and yield outputs with those obtained from two large-scale experiments where multiple observations of leaf area index, mass, nitrogen and yield were measured. The correlation between observed and simulated LAI, mass, nitrogen and yield were 0.76, 0.96, 0.94 and 0.97, respectively. Chimonyo *et al.* (2016) also performed validation by comparing the yield results from the field experiments with the results produced by the model and discovered that the model performance was satisfactory, although there was an overestimation of cowpea yield due to the slight overestimation of the biomass.

3.2 AB modelling and simulation

AB modelling is a modelling technique that uses agents which behave autonomously (i.e. no central control) and interact with each other in a given environment (Heath and Hill, 2014, Railsback and Grimm, 2019a). These agents can represent humans (Schelling, 1969), biological cells (Walker *et al.*, 2004), or self-driving vehicles (Martinez and Viegas, 2017), amongst others.

3.2.1 History of AB modelling

According to Heath and Hill (2014), the history of AB modelling can be traced back to the 16th century when Adam Smith developed the idea of *The Invisible Hand* as a metaphor for the apparent emergent behaviours of economic systems. Each individual was assumed to make decisions that would maximise the individual's satisfaction, resulting in the community benefitting from the decisions made by each individual. In the 17th century, Charles Darwin developed the theory of evolution and natural selection, which attempted to explain how complex organisms emerge from the interaction between simpler organisms. In the 1950s, Von Neumann developed a theory of self-replicating organisms called cellular automata (CA) (Sarkar, 2000). In the 1960s, John Conway used CA to create Conway's Game of Life (Bays, 2010). The system did not use a computer; instead, it used a board with pieces occupying different positions. Each piece was either *alive* or *dead* depending on the number and states of its neighbours (Bays, 2010). In the 1960s, Schelling (1969) created one of the first ABMs, which modelled how individuals tend to have housing close to other people of a similar ethnic group. The model showed how interactions between members could result in segregation.

Researchers have used AB modelling in many disciplines, including social sciences, archaeology, and epidemiology. In economics, AB modelling was used to explore new markets, such as the space tourism market (Charania *et al.*, 2006) and existing markets, such as in (Arthur *et al.*, 1996), where they explored whether humans make rational decisions in the stock market and if the market is efficient. In archaeology, AB modelling has been used to research how urbanisation affected communities during the Bronze Age in Mesopotamia (Wilkinson *et al.*, 2007). Quite recently, AB modelling was used to model the transmission of the COVID-19 virus in various facilities to provide recommendations to slow its spread (Cuevas, 2020).

3.2.2 Components of ABMs

According to Macal and North (2010), ABMs are mainly composed of three parts, namely, *agents*, agent *relationships* and an *environment*. The following section explains these parts in detail.

Agents

Agents behave independently and interact in the model, generating emergent patterns. According to Macal and North (2010) and Sayama (2015), agents have multiple characteristics, which include:

- Autonomy: Agents behave independently according to the information they obtain from their surroundings and behaviours controlling their actions.
- State: Each agent has a state that is a collection of attributes that change as the model is run and affect a model's actions.
- Self-contained: This characteristic implies that each agent is a distinct entity with a state likely to differ from that of other agents.
- Social: Agents interact amongst themselves and can compete for resources.
- Adaptive: An agent can learn from experience and alter its behaviour.

Another important aspect of agents is that they have behaviour. According to Crooks and Heppenstall (2011), agent behaviour is usually rule-based. However, it is difficult to represent all human behaviour using this approach; hence, some studies incorporate complex frameworks such as the Theory of Planned Behavior (TPB) (Lin *et al.*, 2022).

Agent relationships and interactions

Agents' relationships play a role in the way agents interact. The relationships determine the set of agents to which each agent is connected (Macal and North, 2010). The topology of an ABM specifies the *connectedness* of the agents, with some ABMs utilising multiple topologies. Examples of topologies used in ABMs are:

- Grid topology: This is the simplest topology and is composed of a grid similar to that used in CAs.
- Network topology: The topology has links between different agents, which typically represent social relationships.

- GIS: This uses geographic locations of various features such as buildings, roads and rivers.
- Aspatial topology: The agents' locations are not considered, and the model selects random agent pairs that can interact.

Importantly, agents utilise the information that is available locally to make decisions. In addition, each agent can only interact with other agents close to the agent according to the topology used by the model.

Environment

The environment is closely linked to the topology. An environment facilitates both the agent-agent and agent-environment interactions by providing information such as the location information of agents (Crooks and Heppenstall, 2011, Railsback and Grimm, 2019b).

In addition, the environment can affect agents' behaviour (Macal and North, 2010). For example, in models that use a grid environment, each section might have a value of biomass associated with it. If a forager agent is on a section of the grid with low biomass and the agent needs to feed, the forager would have to move to another section in search of food.

3.2.3 Methodology for developing ABMs

Loper (2015) described steps to be followed when developing models and simulations. The stages include defining the problem to be solved, developing the conceptual model, data collection and analysis, implementation of the model, verification and validation, designing experiments, analysing output, configuration control and developing documentation. These steps are discussed below in more detail.

3.2.3.1 Defining the problem

Before a model is developed, the problem that needs to be solved has to be defined precisely. According to Loper (2015), both the client and modeller have to agree on the problem, and the problem will evolve as new requirements emerge and more information becomes available. The problem can be broken down into scenarios, which will be explored through simulations.

3.2.3.2 Developing the conceptual model

The conceptual model is a simplified representation of the system that is being modelled. There are two types of conceptual models, namely, informal and formal conceptual models (Loper, 2015). Both types are meant to be understood by humans. Informal conceptual models can be expressed using general written language, showing what will be considered in the final model. Formal conceptual models are more precise than informal conceptual models, and according to Turnitsa (2015), these can be expressed using the different Unified Modelling Language (UML) diagrams (Eriksson *et al.*, 2003). In general, conceptual models are composed of *objects*, which are the entities in the system, *processes*, which are activities that change the system and *relations*, which show how the different objects interact.

3.2.3.3 Data collection and analysis

Data is collected during the development of the conceptual model (Loper, 2015). The data is used as input data into the model and comes from various sources, including historical and observation data. The data can be used directly by the model, or it can be used to create probability distributions, which can generate data for the model.

3.2.3.4 Implementation of the model

In the implementation stage, the modeller converts the conceptual model (usually the formal conceptual model as it is more precise) into a form a computer can compile and run (Loper, 2015). A modeller can choose the methodology they want their model to follow. This involves deciding between discrete events or continuous simulations and whether the model will use agents. The modeller can implement the model using a programming language such as Python or a simulation language such as Cormas (Bousquet *et al.*, 1998). Implementing a model using a programming language is more difficult and takes longer than implementing it with a simulation language. However, implementing a model using a programming language allows for easier model customisation than using a less flexible simulation language.

3.2.3.5 Verification and validation

According to Loper (2015), verification refers to checking whether the model follows the specifications of the conceptual model. It is an ongoing process, achieved by utilising the debugging facilities of the programming environment. On the other hand, during validation, the model is checked to determine the extent to which it represents the real-world system.

A strategy that can be used in verifying models in large projects is to build two models and compare the models' outputs, which should match. If the outputs do not match, the source of the discrepancy must be identified and corrected. Alternatively, the model can be validated by comparing its output data with historical data from the real-world system. Similar to validation, verification is performed at every step of modelling.

3.2.3.6 Designing experiments

In this stage, the experiments for exploring the scenarios are designed (Loper, 2015). The initialisation, simulation duration and number of runs per simulation of each scenario are determined. For simple models, only one of the model input parameters can be varied during each simulation. However, for more complex models, statistical approaches such as the design of experiments (DoE) and Monte Carlo analysis could be used in designing the simulation experiments.

3.2.3.7 Analysing output

The model runs are analysed using measures of performance (MOP) (Loper, 2015). MOPs show how the model behaves when run with different scenarios through a measurable quantity. The simulation results can produce outlier results, which need to be checked as they could be caused by a bug in the model.

3.2.3.8 Configuration control

According to Loper (2015), the *configuration* of a model is the collection of all the components of a model. This collection could be made up of multiple files, and it is important to store a version

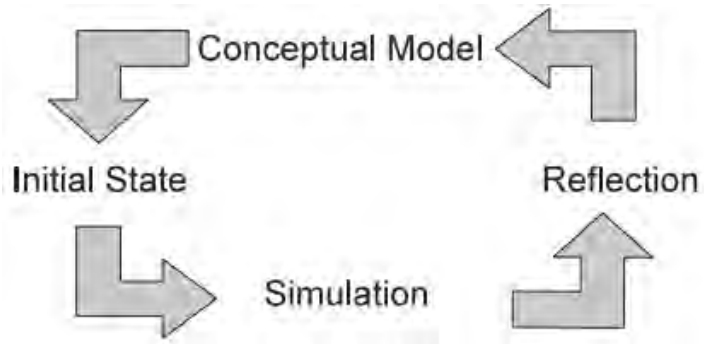

Figure 3.1: The modelling stages using the ComMod approach – taken from Farolfi *et al.* (2010)

of the model that has passed the required tests through the process of *configuration control*. The modeller will modify a separate copy of the model, and if the modeller wants to use a previous version of the model, they can easily do that as it would have been preserved.

3.2.3.9 Developing documentation

Documentation is critical as it allows the model to be reused by another modeller (Loper, 2015). Documentation would include information about the input data, including its format and the model results.

3.2.4 Development tools for ABMs

Multiple tools and techniques can be used by researchers in the development of ABMs. These range from methodologies such as Companion Modelling (ComMod) that allow for the co-designing of ABMs, ODD protocol that allows researchers to document how they developed their ABMs to implementation software for developing ABMs such as NetLogo and Cormas (Allan, 2010).

3.2.4.1 Companion modelling

ComMod is an iterative and participatory methodology researchers use to build ABMs to discuss natural resource sharing among stakeholders (Barreteau *et al.*, 2003).

Figure 3.1 shows the stages followed by researchers following the ComMod approach when modelling. According to Farolfi *et al.* (2010), the first stage of the process involves building the

conceptual model, with ARDI (explained in the following section) being an important tool in the process. The data required to implement the model is gathered in the second stage. The third stage involves converting the conceptual model into an ABM or a Role Playing Game (RPG). During the fourth stage, the RPG or ABM is utilised in stakeholder discussions to validate the tools and explore future scenarios. The cycle is then repeated by taking into consideration feedback from the stakeholders.

3.2.4.2 The ARDI method

Etienne *et al.* (2011) developed the ARDI methodology for co-creating models for natural resource management with various stakeholders. In ComMod, stakeholders must agree on a conceptual mental model of the system. The ARDI method facilitates the creation of a shared mental model amongst the stakeholders. Participatory modelling requires stakeholders to have a shared understanding of their system. The developers of the ARDI method wanted a system that stakeholders could follow to have a shared understanding of the system.

ARDI stands for *Actors*, *Resources*, *Dynamics*, and *Interactions*, the four stages followed when doing the exercise (Etienne *et al.*, 2011). Researchers using this method must choose the participants carefully to avoid overrepresenting any particular group. One key aspect of the selection is reducing the number of powerful stakeholders to allow for a fairer outcome. The selected participants must agree on the question they want to solve. The researchers can also split this question into multiple questions, and the questions would act as an anchor for all the discussions that would take place.

The first phase of the ARDI process is the identification of critical actors. According to Etienne *et al.* (2011), the selected stakeholders can perform the first phase in three steps. In the first step, the participants list the crucial stakeholders and their links in the question context. These stakeholders could be direct stakeholders or indirect stakeholders. Direct stakeholders are those usually located in the study area and who directly influence processes that affect the system. Indirect stakeholders are generally located outside the study area but have power over the activities of the direct stakeholders. This influence can be in the form of regulation or funding.

In the second step, the workshop facilitator asks the participants to refine the links identified. If any actors are not linked to other actors, the facilitator would ask the participants if they want

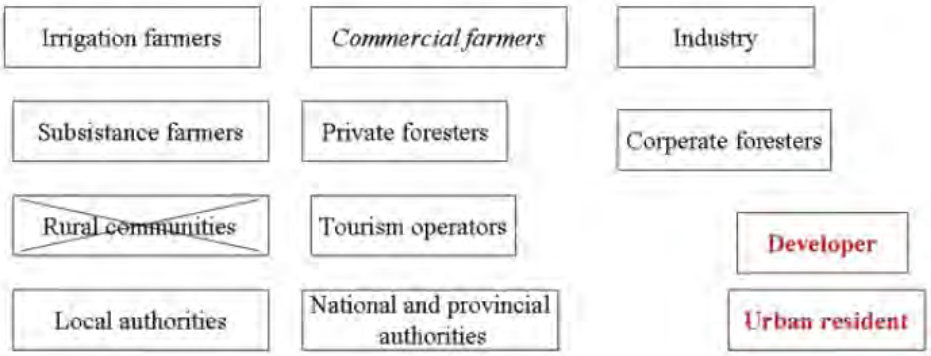

Figure 3.2: An actors diagram for the Crocodile Catchment. The facilitator added the items in red because the participants were unable to find a term encompassing the animals farmed near the river – taken from Etienne *et al.* (2011)

to keep or remove the actors. In the third step, the facilitator asks the participants to identify the entities each direct stakeholder manages. These entities could be dams, fields or cash. The result of this stage is an actors diagram.

The researchers applied the ARDI method in the Crocodile Catchment, where the researchers wanted to identify the primary resources, agents and processes that affected the flow of the Crocodile River (Etienne *et al.*, 2011). Figure 3.2 shows the actors in the region. The facilitator formulated words in italics and then added the words in red later in the ARDI process. An interesting thing to note is the crossed actor Rural communities. The facilitator crossed them out because the water abstracted from the river by Rural communities was negligible compared to the water abstracted by the other actors.

The second phase of the ARDI method is identifying key resources (Etienne *et al.*, 2011). Similar to the first phase, participants list the resources each actor uses. Participants must justify why they have suggested a resource and mention the characteristics of the resources the actors consider when making decisions. For example, if a participant mentions water is a resource, they would add features such as water quality and volume, as these are some of the attributes actors consider when deciding about water.

Figure 3.3 shows the resources participants who participated in the Crocodile River ARDI process identified. The resource Farmed animals is red because the facilitator added it as the participants struggled to find a term encompassing the animals farmed near the river.

Identifying key processes is the third phase of the ARDI process (Etienne *et al.*, 2011). The

Figure 3.3: Resources identified in the Crocodile Catchment – taken from Etienne *et al.* (2011)

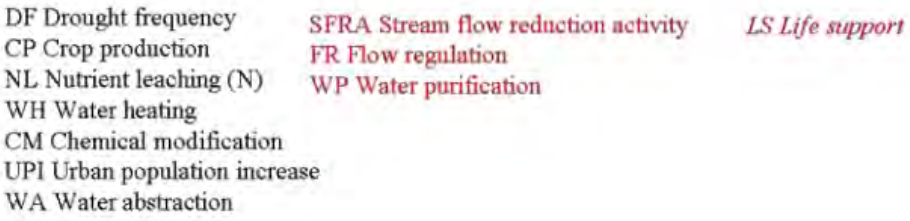

Figure 3.4: Processes identified at the Crocodile River – taken from (Etienne *et al.*, 2011)

participants list all the processes relevant to answering the question. If the list is long, the facilitator requests each participant to rate ten processes they feel are the most important. Each participant gives the value *ten* to the process they think is the most important whilst giving the value *one* to the process they feel is the least important. The facilitator then chooses the overall top processes given each participant's ranking of the processes.

Figure 3.4 shows the processes identified by the participants. Like the earlier diagrams, the facilitator added red processes during the ARDI processes that followed and suggested the process in italics.

According to Etienne *et al.* (2011), eliciting interactions is the fourth phase of the ARDI method and the longest phase. The facilitator asks the participants to add interactions between the identified stakeholders and resources or between two stakeholders. The links should be verbs, and the participants add the information a stakeholder would use when acting. This stage aims to create an interaction diagram representing the shared conceptual model.

In Figure 3.5, the green boxes are resources; the white boxes are actors; the blue text represents actions, and the letters in bold represent processes.

After the stakeholders have developed the interactions diagram, the stakeholders can then discuss a management plan, or the researchers can implement a computer simulation model or RPG

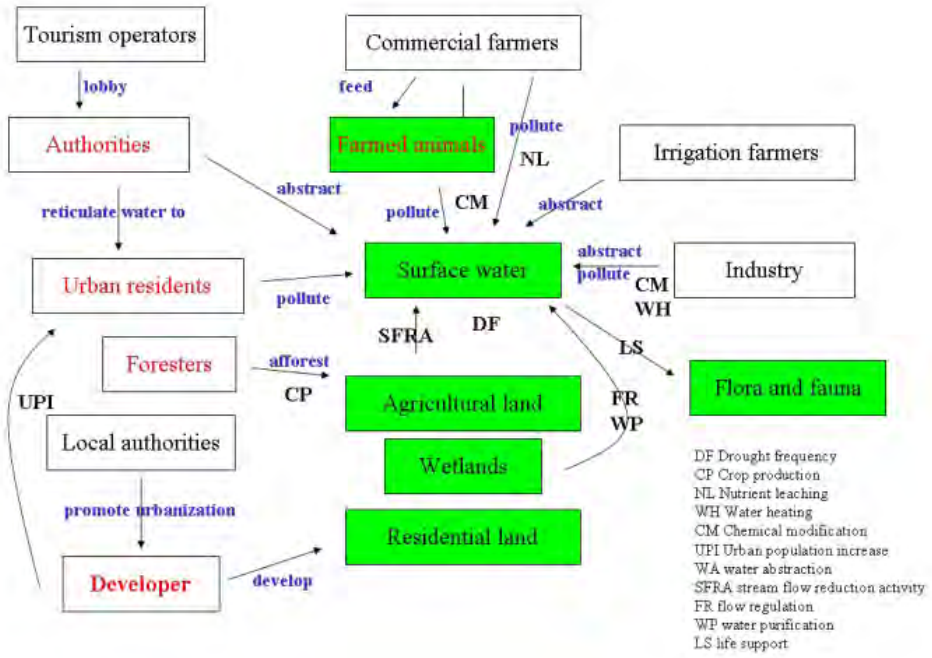

Figure 3.5: Interactions between entities at the Crocodile River – taken from Etienne *et al.* (2011)

that the researchers could use to discuss resource management strategies with the stakeholders (Etienne *et al.*, 2011). The ARDI process results in the creation of a shared mental model amongst the stakeholders. Differences in individual and shared mental models can also be identified by researchers using the ARDI method.

Although ARDI is a useful method, there are some limitations associated with it. The method requires skilled facilitation because some discussion topics can be sensitive and might lead to conflicts (Etienne *et al.*, 2011). The facilitator must ensure that the stakeholders are comfortable sharing their perspectives. This method needs the proper representation of participants of different types depending on the question. Another issue with this method is that the participants must agree on the question they are trying to solve.

3.2.4.3 ODD protocol

Documenting models is an important aspect of AB modelling. According to Grimm *et al.* (2006), many ABMs do not have comprehensive documentation that is easily understandable. To solve

this problem, the authors developed the Overview, Design Concepts and Details (ODD) protocol. This protocol sought to standardise the documenting of ABMs in ecology.

However, one of the weaknesses of the ODD protocol is that it does not include human decision-making. Müller *et al.* (2013) developed the ODD + D protocol (with the '+*D*' representing human decision-making) by modifying the ODD protocol to include human-decision making. In addition, the authors made general improvements to the ODD protocol, such as specifying the model user and describing how space was represented in a model. The authors developed guiding questions to facilitate the development of the ODD + D protocol. The protocol comprises three main parts: the *overview*, *design concepts* and *details* sections.

The overview section provides details regarding the aim of the ABM. The section describes the types of entities in a model, including agents and the smallest representation of space. The various external factors, such as rainfall that affect the state variables of the entities are included in this section. The order in which processes occur in the model is also described (Müller *et al.*, 2013).

The design concepts section deals with information regarding aspects of the model, such as the theories that support the model and how individual agents sense their environment (Müller *et al.*, 2013). Some of the other aspects of the model covered in the concepts section are agent–entity and agent–agent interactions, how agents predict future events and an explanation of parts of the model that use random data, e.g. market prices.

The details section of the ODD + D protocol contains information about tools used to build the model and the location of the source code on the Internet. Other information in this section considers the method used to initialise the model, the type of input data and a detailed mathematical description of the various sub-models used.

Müller *et al.* (2013) applied the protocol when documenting a water use ABM. According to the authors, the ODD + D protocol greatly assisted readers of ABMs' documentation. Furthermore, the protocol could be used by researchers when conceptualising and building ABMs.

UML diagrams can be used when developing conceptual models and creating documentation for models. UML is a set of diagramming techniques used when developing software (Eriksson *et al.*, 2003). Multiple UML diagrams are used in agent-based modelling, including class, activity, and sequence diagrams.

A class diagram is a representation of the various entities in a system. Each class has a unique name and a set of attributes and methods. The classes are linked according to their relationships, e.g., one class could be a specialized version of another class (Eriksson *et al.*, 2003). An example of a class can be a vehicle class. The vehicle class would have various attributes, such as colour and fuel consumption. Specialised versions of a vehicle class can be a car, bus or a van.

Activity diagrams describe steps that a system follows during a process. An activity diagram has diagrammatic symbols representing decision points, i.e., the system checks certain conditions before executing other processes. Sequence diagrams show how objects (instances of classes) interact in the system. The diagram shows the messages being sent between objects, with time represented using the vertical axis (Eriksson *et al.*, 2003).

3.2.4.4 Implementation platforms

Participatory modelling requires a platform that allows stakeholders to be involved in the design of the ABM. Bommel *et al.* (2016) developed the Cormas platform (Common-Pool Resources and Multi-Agent Systems), which was implemented using VisualWorks Smalltalk. In addition to having a platform that researchers could use to run and analyse the results of a scenario, the developers of Cormas wanted a platform that would make it easier for stakeholders to co-design ABMs with researchers. The developers also wanted the platform to run hybrid simulations whereby stakeholders would make some decisions while the model is executed on a computer. Cormas has been widely used to model the interaction between humans and ecosystems (Allan, 2010).

According to Bommel *et al.* (2016), the Cormas platform has three main classes, namely, *social agent*, *spatial agent* and *passive entity*. When modellers implement models, they must decide to which category each agent belongs. For example, if a model has a Hunter agent, the Hunter agent can be defined as a social agent. That way, the agent can reuse methods like the moveTo method already defined in the social agent class.

The Cormas platform has an executable activity diagram that allows users to modify agent behaviour before or during a simulation (Bommel *et al.*, 2016). The activity diagrams have limited functionality because their primary purpose is to allow inexperienced users to make or suggest modifications to the model, thereby improving its effectiveness as a collaborative tool.

Researchers can use the Cormas platform to perform sensitivity analyses where changes in model input parameters and their effect on the model's output are analysed. Various sensitivity analyses can be performed using Cormas, such as One Factor At a Time (OAT), where one parameter is changed at a time; simple stochastic, where certain input parameters are varied randomly but individually; and cross-analysis, where multiple input parameters are varied at the same time.

NetLogo is another ABM implementation tool. According to Allan (2010), NetLogo uses a language called Logo, a form of Lisp. Unlike Cormas, NetLogo was designed to develop models that could be easily accessible over the Internet.

Another platform for implementing ABMs is the Multi-Agent Research and Simulation system (MARS) (Hüning *et al.*, 2016). Like NetLogo, the MARS platform is suitable for developing models that can be deployed on the Internet. The platform has been used to create multiple models. One of the models developed using MARS showed the interaction between Marula trees and elephants. One aspect of the MARS platform that stands out is the idea of a *layer*. A layer in MARS is a representation of part of the environment. For example, the model modelling the interaction of elephants and Marula trees included three types of layers, namely, the *Basic layer*, *GIS layer* and a *TimeSeries Layer*. The Basic Layer contained data about the location of elephants, water points, and tree agents. The GIS Layer had data about geographic features like mountains, and the TimeSeries Layer had data about soil water and temperature.

3.2.5 Applications of ABMs

This section describes different applications of ABMs. These applications include studies of social-ecological systems (SESs) (Dressler *et al.*, 2019, Smajgl and Bohensky, 2013, Parker and Meretsky, 2004), and investigating measures to reduce the spread of COVID-19 (Cuevas, 2020).

According to Schlüter *et al.* (2021), applications of AB modelling in SESs can be classified into three groups: those exploring emergent behaviour, those used as decision support tools (DSTs) in developing new policies and those used as tools in collaborative exercises amongst multiple stakeholders. Several researchers studying SES problems have used AB modelling because ABMs allow for the emergence of patterns from agent behaviour. In addition, the ABMs can be used by researchers when interacting with stakeholders to co-design solutions to problems.

3.2.5.1 ABM for exploring edge-effect externalities

An example of the use of AB modelling in exploring emergent behaviour is the study by Parker and Meretsky (2004) on how socioeconomic factors determine land-use patterns. The authors implemented the model using the Mathematica software package and measured the landscape patterns using FRAGSTATS. In the model, each agent owns land that can be used as agricultural or urban land. The authors represent each piece of land by a single cell. A cell's location determines its profitability for agricultural or urban use. For example, if agricultural land is located next to urban land, the agricultural land's productivity is reduced. This rule matches how agricultural activities are scaled down close to urban areas for various reasons, including noise reduction and reduced insect populations. On the other hand, the agents can avoid having urban land close to other urban land users, reflecting how property value in urban areas is inversely proportional to residential density.

The authors ran the model and discovered that land use fragmentation caused economic inefficiency. They also demonstrated how negative externalities result in urban sprawl. A critical limitation of the study was that agents could not buy or sell land.

3.2.5.2 The SimPaSI ABM

Smajgl and Bohensky (2013) used AB modelling to determine how an increase in fuel cost in East Kalimantan, Indonesia, affects poverty and deforestation levels. Unlike the study by Parker and Meretsky (2004), Smajgl and Bohensky (2013) utilised participatory modelling to develop an ABM called SimPaSI. Participatory modelling involved the stakeholders in building the SimPaSI model and learning more about the various social and ecological issues affecting the East Kalimantan residents. The authors used survey results from 3000 households and clustering to obtain the agent types. The clustering process showed 19 unique agent types, and the authors then conducted interviews to determine the agents' behaviour in each group.

Households are the primary agents, and these need to obtain their income goals (Smajgl and Bohensky, 2013). The SimPaSI model utilises GIS data, and the environment directly influences the behaviour of the households. If a household is located close to a river or a lake, the household members practice fishing, whereas those close to the forest practice logging. The model uses daily timesteps, and the rainfall is based on historical data at each timestep.

In the SimPaSI model, the amount of rainfall controls how vegetation grows. At a weekly timestep, the household members engage in various economic activities like logging and fishing, which provide income. Households can also choose the economic activities they wish to partake in and can even choose to migrate. Different submodels, such as models controlling crop market prices, hydrology and fish, are included. The emergent data is the number of households whose income is below the poverty line, the households' locations, and the level of natural resources.

The authors found that reducing fuel prices resulted in a slight decrease in poverty levels (Smajgl and Bohensky, 2013). A decrease in fuel prices of more than IDR 1000 (IDR is the currency of Indonesia) results in a severe reduction in resources such as fish because activities such as fishing require fuel, and a lower fuel price encourages more people to fish, leading to a decrease in the fish population. Due to these findings, the authors suggested that the government should not decrease fuel prices by more than IDR 1000. The model also showed the stakeholders that poverty occurs not only in rural areas but is dynamic and can spread into urban areas.

A limitation of the research was that the clustering analysis could not sort the households into different groups. The researchers had to rely on local experts to place the households into the groups. The ComMod approach has the problem of bias from the different stakeholders being introduced into building the model, and the authors combated this problem by interacting with local researchers and holding workshops (Smajgl and Bohensky, 2013).

3.2.5.3 An ABM for studying the impact of different pastoral behaviour

According to Dressler *et al.* (2019), many communities are threatened by unsustainable pastoral practices that lead to overgrazing and environmental degradation. The authors developed an ABM using NetLogo to investigate how changes in human behaviour affect pastoral communities.

The model has agents representing households with attributes such as the number of livestock, location, and behaviour regarding livelihood practices (Dressler *et al.*, 2019). There are three types of behaviours. Firstly, *traditionalist* behaviour meaning that a household follows social norms such as maximising the number of livestock whilst ensuring the pastures are not degraded. The second behaviour is *profit maximiser*, which causes a household to maximize profits by not following social norms and choosing grazing areas with the highest biomass. The third behaviour

type is the *satisficer* behaviour, whereby a household limits the number of livestock it owns and supplements its livelihood needs by partaking in other economic activities.

At each annual timestep, the model generates rainfall and increases the green biomass of the vegetation. The livestock reproduces, and the households search for pasture for their animals. The agents use rules for searching and increasing the number of livestock based on their behaviour category. For instance, profit maximising agents would select the patch with the highest amount of biomass and not follow any social norms. The maximum number of livestock these agents can keep is only limited by the amount of pasture available. On the other hand, agents with the other behaviour types have an individual limit to the number of livestock they can keep, and they are affected by social norms. If more agents allow the vegetation time to recover, a satisficer agent would be less likely to select patches of vegetation with biomass below a certain threshold so that the vegetation could recover. However, profit maximising agents do not consider social norms and typically select patches with the highest biomass. After the patches have been selected, destocking occurs if the biomass chosen by a household agent is insufficient to feed the livestock. Households with no livestock at any stage of the simulation are removed from the system (Dressler *et al.*, 2019).

The authors ran multiple scenarios. The indicators they considered were the total number of households, the total number of livestock and the total reserve biomass. The first set of scenarios considered what would happen when all the households had the same behaviour type. For each scenario, the researchers set the total number of households to 90 and ran each scenario 100 times for 100 timesteps. The scenario with agents with the traditionalist behaviour type resulted in the elimination of 35% of households, but none of the households in the profit maximiser behaviour type scenario were eliminated. This is because households with profit maximiser behaviour did not consider the reserve biomass before selecting patches; therefore, they always found patches for their livestock to graze. On the other hand, households with the traditionalist behaviour type would not select patches whose biomass was lower than the reserve biomass, which meant some households would not find patches for their livestock and were eliminated from the simulation.

However, the scenario with households with the traditionalist behaviour had the highest number of livestock, and the scenario with the satisficer behaviour had the second highest number. Regarding the total amount of reserve biomass, the scenario with households with the traditionalist behaviour had the highest reserve biomass and the scenario with the profit maximiser households

had the least reserve biomass.

In the second set of scenarios, the researchers increased the number of profit maximiser households compared to the traditionalist households. The authors discovered that an increase in the proportion of profit maximiser households resulted in more traditionalist households losing all their livestock, or the traditionalist households would become less likely to follow social norms, leading to overgrazing.

3.2.5.4 An ABM for studying the spread of COVID-19

Similar to the research undertaken by Parker and Meretsky (2004) that provided policy suggestions, Cuevas (2020) developed an ABM to investigate measures that could be used to slow down the spread of the COVID-19 virus when people are using various facilities.

In the model that Cuevas (2020) developed, there are two agent types, A agents, which represent agents that have not been infected with the virus and B agents, which are agents that are already infected with the virus. Type A agents have various attributes, which include *Pri* representing the probability of an agent getting infected. Both types of agents have an attribute called mobility probability *Prcm*, which is a measure of the mobility of each agent. If the value for Prcm is close to one, it means the agent has high mobility; if the value is close to zero, it means the agent has low mobility.

The agents' behaviour is governed by two rules (Cuevas, 2020). The first rule describes the transmission of the virus, controlled by the parameter R, which is the minimum distance between an agent of type A and an agent of type B for transmission to be possible. The second rule determines how the agents move in the environment and uses the *Prcm* attribute.

The initialization step involves setting the number of A and B agents. The agents are placed at random positions in a two-dimensional environment. The model randomly generates Pri values in a range specified by the model user and assigns the values to each A agent. The model also assigns Prcm to all agents, similarly to the Pri values. In the model, rule one is executed for all agents and then rule two is executed. The process is repeated until the maximum number of steps is reached. The model visualises the agents, showing infected agents as red and uninfected agents as blue circles.

Cuevas (2020) ran multiple scenarios. In the first scenario, the baseline, there were 500 agents of type A and one of type B. The Pri values for all the type A agents ranged from 0.1 to 0.3, and the Prcm values for all agents were between 0.2 and 0.4. R was assigned the value 1. The researcher ran the model for 500 steps and discovered that the infection rate peaked at the 150th step, and all agents were infected at the end of the simulation.

In the second scenario, the author varied the number of type A agents from 10 to 1000 and found that transmission rates were lower when there were 100 or fewer agents of type A, and if the number of type A agents were 300 or more, the transmission rates would be high and constant for all values. In the third scenario, the author wanted to determine the effect of preventative measures such as wearing masks and washing hands frequently. To do this, the author created two groups of type A agents, with the first group having higher transmissibility than the second group. The author found that if the proportion of agents in the second group were 60% or higher, the infections would be very low. In the fourth scenario, the author wanted to test the hypothesis that restricting movement would lower the number of transmissions. The researcher eliminated long-distance movement by the agents and found that the number of infected agents at the end of the simulations was much lower when long-distance movement was eliminated than when it was not, and infected agents were located in one region.

3.3 Studies using ABMs for modelling water usage in catchments

AB modelling has been used in multiple studies that model water consumption. The aims of these studies varied and included use of ABMs as DSTs in policy formulation (Lin *et al.*, 2022, Smajgl and Bohensky, 2013), determining how cooperation or lack of cooperation affects water availability (Becu *et al.*, 2003, Khan *et al.*, 2017) and stakeholder engagement using participatory modelling methodologies such as ComMod (Farolfi *et al.*, 2010, Gurung *et al.*, 2006, Smajgl and Bohensky, 2013). Some studies combined ABMs with hydrological models (Khan *et al.*, 2017, Lin *et al.*, 2022) to represent the hydrological processes more accurately. Various aspects were considered, such as stakeholder engagement, spatial representation of the catchments, hydrologic processes, and water demand and consumption determination.

3.3.1 MAS for Kat River Valley

The ComMod approach to modelling was adopted by Farolfi *et al.* (2010) in developing a multi-agent system (MAS) tool for the Kat River Valley located in South Africa, that the authors used to discuss water-sharing scenarios in the region with the stakeholders. In doing so, they also wanted to improve the modelling stages of the ComMod methodology. The study set out to ascertain how various water-sharing strategies under different development trajectories would affect the employment rate, the minimum water level in the river and farmers' income from crop production. The main stakeholders were small and large-scale farmers, domestic water users, and the municipality of Nkonkobe. Some of the agents in the iterations of the KatAWARE model were the Village, Farm and Farmer. In the study, the authors used an iterative methodology in which they had workshops where they met the stakeholders and obtained more information about the system's dynamics and what the stakeholders wanted the model to show. The authors then used the information to develop the new model and run simulations. The researchers presented the model and the simulation results to the stakeholders for feedback and made a further iteration using the new information. The authors discovered that UML is insufficient when designing an ABM, so they made some modifications and introduced new constructs. The study also showed that the iterative approach successfully encouraged the stakeholders to invest in the discussions on how they could share water.

3.3.2 CATCHSCAPE model

According to Becu *et al.* (2003), the region Mue Uam catchment in northern Thailand suffered from water sharing problems. Downstream farmers suffered from water scarcity due to high upstream water consumption. To address this problem, similar to the KatAware project, Becu *et al.* (2003) developed the CATCHSCAPE model, which the authors planned to use in negotiation meetings with the stakeholders. The indicators of interest in the study were each farmer's economic position, i.e. the amount of money each farmer had, land use change and water availability. Some of the agents used in CATCHSCAPE are Manager, Farmer and Crop.

The authors created multiple scenarios. The first scenario was the baseline scenario where Farmer agents could not expand their farming areas by transforming forest land into farm plots, the Farmer agents did not steal water, and the Manager agents cooperated fairly (Becu *et al.*, 2003).

The simulation showed that the wealthy farmers got richer, and the poor farmers became poorer. In the second scenario, Managers did not cooperate, resulting in downstream Farmers reducing their irrigated cropping due to decreased water availability. In the third scenario, the Farmer agents would steal water, i.e. they would extract more water from the canal than was allocated to them by the Manager. This behaviour by Farmers resulted in more Farmers becoming poor. The fourth scenario involved a decrease in water availability, and the results were similar to that of the third scenario; however, in the fourth scenario, the Farmers had less money after a 10-year simulation run than they did in the third scenario.

3.3.3 Limbukha model

According to Gurung *et al.* (2006), Bhutan's economy relies on agriculture and historically, water sharing for agriculture was guided by tradition, which allowed for biodiversity conservation. However, an increase in commercial farming brought pressure on water resources. The researchers did the research to hold negotiations amongst the stakeholders of the Lingmuteychu Watershed in Bhutan on how they could sustainably share the water resources and reduce conflict. The researchers gathered data regarding how the stakeholders of the Lingmuteychu Watershed used water resources. This data came from various sources, such as literature reviews and informal interviews with some farmers. The authors also designed a questionnaire they sent to each household in the watershed. The authors followed the ComMod process. The researchers then used the information they collected to design a role-playing game (RPG) representing two villages: one upstream village called Limbukha and one downstream village called Dompola.

The researchers implemented the MAS version of the RPG called the Limbukha model using Cormas. In the model, each cell represents a Plot, the smallest land unit with a size of 0.1 ha. Each Block is made up of a collection of Plots that belong to one Farmer agent. Some of the attributes of the Farmer agent are: *kinship*, which represents the relationships between the farmers, *myLabour*, which represents the amount of labour a farmer has and *myIncome*, which represents the financial position of a farmer. Farmer agents belong to either the Limbukha Village or the Dombola Village. Each Village is an agent with six Farmer agents. The researchers ran multiple scenarios where they varied social networks, level of rainfall and how farmers shared the water (Gurung *et al.*, 2006). The social network refers to the farmers a Farmer agent can communicate with, which can be members in the kinship, all members in the same village or

both villages. The rainfall level can be either low or high, and how farmers share water ranges from just sharing water with relatives to exchanging water for labour or money. The authors executed 36 different scenarios, each of which was run 20 times by varying these parameters.

The authors looked for criteria of a minimum of 12 rice plots and less than seven fallow plots. The other criteria were more than five potato plots, a minimum annual income of $10 000 and the occurrence of at least one exchange for water, with the amount of water not exceeding three units. The researchers assessed the scenarios according to the number of criteria satisfied. The authors found that scenarios where farmers only shared water with family members generally met fewer criteria compared to scenarios where farmers shared water with all other farmers in both villages. Surprisingly, rainfall levels did not impact the number of criteria satisfied by a scenario. Instead, the level of cooperation amongst the farmers was the biggest factor in the viability of a scenario. Similar to the outcome in the study by Farolfi *et al.* (2010), this study was successful as the stakeholders were invested in the ComMod process and committed to sharing water equitably (Gurung *et al.*, 2006).

3.3.4 A framework for coupling ABMs with SWAT

It is important for ABMs modelling water usage in catchments to explicitly represent the interactions between the human and natural systems because linking the two systems allows researchers to understand better how the two systems interact (Khan *et al.*, 2017). The authors developed a general framework that coupled an ABM, implemented using the R language, with a SWAT model. The agents in the ABM are administrative units that can make water management decisions depending on the ranking of agricultural production, ecology conservation, and hydropower generation. Similar to agents in the CATCHSPACE and Limbukha models, the agents in this ABM can interact and share water. The *level of cooperation* (LOC) parameter determines the probability of an agent cooperating with another agent with values ranging from 0 (no cooperation) to 1 (agent always cooperates).

The researchers applied the framework in two case studies, the Mekong River basin in Asia and the Niger River basin in Niger. In the first case study, the authors wished to demonstrate how agents' ranking of water uses affected other water uses. The authors discovered that if an agent prioritised crop production, the total crop production after executing the simulation for 25 years

would be higher than one where that agent's crop production has the lowest priority. The agents' preferences had no significant impact on the health of the ecology due to reservoirs having low storage capacity relative to streamflow (Khan *et al.*, 2017).

The researchers then used the modelling framework for the Niger River basin to show how the cooperation between the agents affected the emergent outcomes. The authors used 26 years as the period of the simulations and assigned 1 for the LOC of all agents in one scenario, meaning there was maximum cooperation. In the other scenario, the authors set 0 for the LOC for all agents, meaning agents only made decisions to satisfy their goals and would not cooperate. In the full cooperation scenario, additional water releases by upstream agents did not necessarily produce more crop production output, as other factors could affect crop production.

3.3.5 Planned behaviour model

Using rule-based decision-making algorithms in ABMs does not accurately represent how human agents make decisions, especially when there is incomplete data on which to base the decisions (Hyun *et al.*, 2019). To implement ABMs in which human agents follow rule-based algorithms, researchers must interview the stakeholders and run surveys, which is time-consuming, and it is difficult to ask all the necessary questions to understand the decision-making process. Hyun *et al.* (2019) wanted to develop a framework that would allow them to create ABMs that are not reliant on the rule-based system.

To achieve this, Hyun *et al.* (2019) applied the theory of planned behaviour (TPB) in their framework. TPB is used to predict an individual's behaviour by considering various factors. The factors include the individual's perception of the behaviour, i.e., whether the individual thinks the behaviour is good or bad, society's view of the behaviour and the degree to which an individual is subject to other forces, e.g., the amount of rainfall and market forces. The authors implemented the TPB using Bayesian Inference (BI) mapping, which calculates the probability of an agent performing a behaviour and updates the agent's beliefs. They also used the cost-loss model (CL) to represent the external factors that affect an agent's decision-making process.

The researchers applied the framework in the San Juan River basin in the USA, where the population relies on the San Juan River for their water needs. The area also has the Navajo reservoir that supplies water for irrigation and domestic use. The authors identified 16 irrigation

ditches in the region and represented them as agents in the ABM. The authors divided the 16 agents into three groups according to their location in the basin. Each group considered different factors when making a decision using BI mapping. For example, agents in group 2 that were located midstream where a major tributary joined the Juan River had the tributary rainfall as one of the factors, whilst the agents in group 1 did not have such a factor (Hyun *et al.*, 2019).

The researchers ran multiple scenarios. Firstly, their calibration results showed that the Nash-Sutcliffe Efficiency (NSE) was 0.55, which was considered suitable. The researchers then modified the risk perception parameter λ from 0.5 to 1. They found that as λ increased, agents took more risks as they placed increased trust in new forecast information. The authors also varied the cost-loss ratio to determine the agents' behaviour in reaction to an increase or decrease in cost when expanding the irrigated area. The authors found that the agents would delay expanding their irrigation area as the cost of increasing the irrigated area increases.

3.3.6 Yakima River Basin models

Lin *et al.* (2022) investigated the effectiveness of coupling an ABM with RiverWare (RW) and the effect of social norms on predicting water use behaviour in the Yakima River Basin, which is located in Washington in the USA. Farming in the region depends heavily on irrigation, with irrigation water being supplied from five reservoirs. The basin has six irrigation districts, each with water allocation rights.

The authors utilised the RW model calibrated for the Yakima River Basin (YAKRW). The YAKRW was responsible for modelling the river flows and policies such as water allocation and water provided to the irrigation districts. The YAKRW model was the baseline model and runs on a daily timestep, using historical data about past diversions to determine how the irrigation districts would request water. The researchers developed two ABMs, which were coupled with the YAKRW. In both ABMs, the agents are the six irrigation districts and the water provided to the agents is determined using YAKRW policies and the ABMs' rules (Lin *et al.*, 2022).

The authors first developed the Coupled-YAKRW model, which combined the YAKRW with the water request ABM, including social norms. In this model, the agents utilise multiple state attributes and parameters in decision-making. The agents use the state variable *Center*, C, a probability indicating an agent's belief about the future water supply. Some of the agents'

parameters are the *Information Source* (*InfoSource*), which is the type of data an agent uses to predict future water supply. The *InfoSource* was the difference between the current precipitation values for each reservoir or total reservoir storage and the historical values. The second model was called Coupled-YAKRW W/o S, and the model did not include social norms.

Similar to Hyun *et al.* (2019), Lin *et al.* (2022) used NSE to determine the performance of the models. The results showed that the coupled models performed better than the YAKRW model, which did not use coupling. However, the difference in performance between the coupled models was not significant, and the authors recommended more investigation into the matter.

3.4 Comparison of the ABMs for modelling water usage

3.4.1 Stakeholder engagement

Participatory modelling has fostered stakeholder engagement when modelling water demand and consumption (Becu *et al.*, 2003, Farolfi *et al.*, 2010, Gurung *et al.*, 2006).

Farolfi *et al.* (2010) used the ComMod process when developing a MAS called KatAWARE for the Kat River catchment in the Eastern Cape in South Africa. Similarly, (Gurung *et al.*, 2006) used the ComMod methodology when discussing water management strategies with the stakeholders of the Lingmuteychu Watershed in Bhutan. Unlike Becu *et al.* (2003), Farolfi *et al.* (2010) held multiple workshops with stakeholders where the researchers ran different water management scenarios to get feedback from the stakeholders so that the researchers could make the model more accurate.

The first version of the tool was KatAWARE version 0, the simplest version of the model (Farolfi *et al.*, 2010). The researchers based their simulations on four scenarios when demonstrating the KatWare version 0 model. In the first scenario, the system would not change, i.e. the farmers would plant the same crops, and water access by the domestic consumers would remain the same. In the second scenario, the domestic consumers changed their water access from the river to collective and indwelling taps. The third scenario involved small-scale farmers changing from cultivating cabbage to cultivating citrus. The fourth scenario involved the expansion of citrus cultivation by emerging and large-scale farmers by 12.23% of the original farming area

each year until they reached a maximum of 2130 ha over ten years. When the model results were discussed with the stakeholders, the stakeholders proposed various changes. One example of suggested changes was that the agents should be able to use the ecological reserve in drought. The stakeholders also wanted the model to explicitly show how water shortage would affect each of them instead of just showing sub-catchment level effects.

KatAWARE version 1 added the improvements the stakeholders suggested, including a detailed budget for each agent to express better how water shortage would affect each agent (Farolfi *et al.*, 2010). The authors repeated the cycle, and from the feedback they obtained from the stakeholders, they created KatAWARE version 2, which they planned to combine with an RPG. The RPG would be a simplified model form, using physical objects to represent parts of the system, such as river flow. The stakeholders would make decisions to satisfy their goals.

Both Farolfi *et al.* (2010) and Becu *et al.* (2003) emphasised that their models were to foster discussions amongst stakeholders and should not be viewed as the outcome. However, unlike Farolfi *et al.* (2010), who followed the ComMod approach and involved stakeholders from the beginning of the modelling process, Becu *et al.* (2003) did not do the same but instead used surveys for data collection but emphasised that they would need to have direct communication with the stakeholders to get information to make the CATCHSPACE model more accurate.

Although Khan *et al.* (2017) did not use participatory modelling in their case studies, the authors developed a web-based platform for the framework that could be used by non-experts which could facilitate participatory modelling. The web-based platform could allow stakeholders to play RPGs similar to how Farolfi *et al.* (2010) were planning to use KatAWARE version 2.

3.4.2 Spatial representation and hydrologic processes

Representing the landscape and the hydrologic processes is important in ABMs for water management. The landscape representation is determined by the smallest area size that could be considered homogenous, e.g., in the Limbukha model, a cell represents 0.1 ha, the smallest land unit (Gurung *et al.*, 2006). Similarly, the smallest landscape unit in the CATCHSCAPE model represents a plot of size 0.16 ha, which is the typical size of plots in the catchment (Becu *et al.*, 2003). These cells can be aggregated to form new entities such as blocks (Gurung *et al.*, 2006) or sub-catchments (Farolfi *et al.*, 2010). Some models simulated the hydrological processes, such

as rainfall, in greater detail than others. The KatAWARE v1 model uses rainfall data from a hydrological model, while the Limbukha model generates either high or low rainfall.

Farolfi *et al.* (2010) developed the KatAware v1 model using a grid of 76 x 61 cells, with each cell being 66.5 ha. The authors then divided the Kat River Valley into 14 quaternary sub-catchments. The authors created the sub-catchments by locating areas with similar ecological reserve requirements. This was similar to how Khan *et al.* (2017) divided the catchment using the framework they developed using hydrological characteristics and management. The researchers determined the natural runoff for each sub-catchment using a hydrologic model that simulated the natural run-off of all the sub-catchments for 70 years (Farolfi and Bonte, 2006). The KatAWARE model then calculated the amount of runoff each sub-catchment provided for the Kat River runoff.

Similarly, Becu *et al.* (2003) represented the Mue Uam catchment in the CATCHSCAPE model using a grid of 44 x 45 cells. The authors wanted to reduce the number of cells used to represent the catchment (presumably to reduce the amount of computation); therefore, they reduced the modelled area to two-fifths of the original size. Similar to Farolfi and Bonte (2006), the developers of the CATCHSCAPE model also used other models to simulate the hydrologic dynamics. However, unlike the KatAWARE model, which used a hydrologic model that only provided the amount of rainfall, the CATCHSCAPE model was linked to two models that modelled the hydrologic processes in greater detail. Becu *et al.* (2003) used a hydraulic model composed of the river and canal system but also linked the CATCHSCAPE model with the CATCHCROP model (Perez *et al.*, 2002) that provided rainfall and runoff and kept track of the amount of water in the soil available to crops.

3.4.3 Determination of water demand and consumption

Multiple factors affect an agent's water demand and consumption. Some of these factors are water use licence, hectarage of crops under irrigation and position along a river.

The KatAWARE model has a *WaterLicence* class with attributes *duration*, *quantity* and *startingDate*. A collection of villages (*municipality*) and the Farmer agents can make requests for a water licence from the Water User Association (*WUA*) (Farolfi *et al.*, 2010). The Limbukha model has a similar water allocation system, but it differs from the KatAWARE v1 model in that the Farmer agents in the Limbukha model cannot apply for a different water licence. In

the Limbukha model, the Farmer agents have the *myWater* attribute, representing the amount of water allocated to a farmer. The attribute's value depends on the farmer's category and the amount of rainfall. There are four categories, namely *thruelpa*, *cheep*, *chatro* and *lhangchu*. Farmers in the thruelpa category have access to most of the water and are entitled to half of the canal's water. Those in the cheep category can access a quarter of the canal's water, with farmers in the chatro group having access to $\frac{1}{8}$ of the canal's water. The farmers in the lhangchu category do not have water allocated to them, and they have to negotiate with farmers in other categories for irrigation water (Gurung *et al.*, 2006).

Like the Farmer agents in the Limbukha model, Farmer agents in the CATCHSCAPE model cannot change the amount of water allocated for irrigation (Becu *et al.*, 2003). In CATCHSCAPE, each farmer's water allocation depends on bamboo pipes attached to the canal and the farmer's fields. The amount of water allocated to each farmer depends on the number of bamboo pipes and the duration for which the farmer can use them.

Farolfi *et al.* (2010) determined the water demand in each quaternary as the sum of domestic and irrigation demand. The domestic water demand depends on the population and the type of water access. A farm's water demand depends on cultivated crop type and hectarage. In the event of water shortage, the domestic supply is satisfied before farms can access the water (Farolfi *et al.*, 2010).

Similar to the calculation of water demand in the KatAWARE model, the water demand by agents in the ABM framework developed by Khan *et al.* (2017) depends on the hectarage of the irrigated area.

3.4.4 Human behavior

The studies included multiple aspects of human behaviour. One such aspect is decision making, which is mostly rule-based (Becu *et al.*, 2003, Farolfi and Bonte, 2006, Khan *et al.*, 2017) or based on BI (Hyun *et al.*, 2019). Other features the studies explored were degree of cooperation (Khan *et al.*, 2017), violation of allocation rules (Becu *et al.*, 2003) and learning from experience (Becu *et al.*, 2003).

Farolfi and Bonte (2006) used rule-based decision-making when modelling how farmers decide the type of crops they wish to cultivate. At the end of each year, the farmers in the KatAWARE

v1 model select the crops to cultivate based on the water licence they have received from the WUA. Similarly, the Farmer agents in the Lumbukha consider the amount of rainfall and market price when making crop cultivation decisions. If the price of 1 kg of potatoes is higher than 6 Nu (Nu is the currency in Bhutan) and the rainfall is normal, the agent will cultivate both potatoes and rice. However, if one of these conditions is false, the agent grows rice only (Gurung *et al.*, 2006).

Some studies also allowed the agents to learn from experience and still use the rule-based decision-making system. In the CATCHSCAPE model, the Farmer agents keep track of the previous year's rainfall in the *water expectation* attribute. They then determine the crops they will cultivate by choosing crops that can be irrigated using the amount of water indicated by the water expectation attribute (Becu *et al.*, 2003). Likewise, the agents in the ABM developed by Khan *et al.* (2017) use the previous year's crop yield to make crop cultivation decisions. In contrast to the models discussed in this section, the agents do not change the type of crops; instead, they would either increase or decrease the area under irrigation. If the previous year's yield is below the threshold set by the target, the agent increases the area they cultivate.

Most of the studies documented used a rule-based approach to agent decision-making; however, Hyun *et al.* (2019) criticised the approach because it does not consider that the information the agents base their decisions on might be incomplete or ambiguous. In light of this problem, Hyun *et al.* (2019) incorporated TPB into their ABM using BI mapping and CL.

The basis of their implementation is the equation:

$$P(f \mid \theta) = \frac{P(f \cap \theta)}{P(\theta)} \tag{3.1}$$

This equation gives the probability of an agent performing a decision θ, which represents an increase in the irrigated area based on the variable f, which specifies the level of a factor relevant to the decision-making. In this case, this factor predicts the next year's water supply. The researchers then derived the following equation:

$$\begin{aligned} P(\theta) = &\frac{P(f \mid \theta) \times P(\theta)}{P(f \mid \theta)P(\theta) + P\left(f \mid \theta^{\mathrm{c}}\right) P\left(\theta^{\mathrm{c}}\right)} \times P(f) \\ &+ \frac{P\left(f^{\mathrm{c}} \mid \theta\right) \times P(\theta)}{P\left(f^{\mathrm{c}} \mid \theta\right) P(\theta) + P\left(f^{\mathrm{c}} \mid \theta^{\mathrm{c}}\right) P\left(\theta^{\mathrm{c}}\right)} \times P\left(f^{\mathrm{c}}\right) \end{aligned} \tag{3.2}$$

This equation determines the probability of an agent making a management decision θ where $P(\theta^{c})$ is the probability of an agent not making that decision. The authors then applied BI theory and also replaced $P(f \mid \theta)$ with λ, $P(\theta)$ with Γ_{pr} and $P(f)$ with Γ_{pd} to give:

$$\begin{aligned}\Gamma_{\mathrm{pr}}^{t} = & \frac{\lambda \Gamma_{\mathrm{pr}}^{t-1}}{\lambda \Gamma_{\mathrm{pr}}^{t-1} + (1-\lambda)\left(1-\Gamma_{\mathrm{pr}}^{t-1}\right)} \Gamma_{\mathrm{pd}}^{t} \\ & + \frac{(1-\lambda)\Gamma_{\mathrm{pr}}^{t-1}}{(1-\lambda)\Gamma_{\mathrm{pr}}^{t-1} + \lambda\left(1-\Gamma_{\mathrm{pr}}^{t-1}\right)} \left(1-\Gamma_{\mathrm{pd}}^{t}\right)\end{aligned} \tag{3.3}$$

This equation shows that an agent's prior belief $\Gamma_{\mathrm{pr}}^{t-1}$ in the previous timestep affects the probability of an agent Γ_{pr}^{t} making a management decision. A risk-avoiding agent has a λ value of 0.5, while a more risk-seeking agent has a λ of 1. According to the authors, multiple factors can affect the likelihood of a management decision, so the agents rank the extent to which each relevant preceding factor deviates from the typical values and choose the highest one when making the decision (Hyun *et al.*, 2019).

In some studies, the agents could share water. In the CATCHSCAPE model, the downstream canal manager agents can request water from the upstream canal managers in a water shortage. The upstream canal manager considers the water shortage ratio between the upstream and downstream farmers before responding to the water request (Becu *et al.*, 2003). Similarly, the administrative unit agents in the ABM developed by Khan *et al.* (2017) can share water; however, unlike the agents in the CATCHSCAPE who consider the water shortage ratios of upstream and downstream farmers before making a decision, the agents use the LOC parameter that determines the probability of an agent cooperating with another agent. In the Limbukha model, each Farmer agent has a social network which represents the set of Farmer agents the agent can request water from (Gurung *et al.*, 2006).

3.4.5 Coupling ABMs and hydrological models

Catchments are complex systems, with human activities affecting catchment processes, which, in turn, affect humans. This feedback loop is important in studying coupled human-natural systems; however, representing all the hydrologic processes in an ABM is arduous. A solution to

this problem is to couple ABMs and hydrological models. Khan *et al.* (2017), Lin *et al.* (2022) and Hyun *et al.* (2019) all used this approach.

Khan *et al.* (2017) combined an ABM with a SWAT model. The authors chose the SWAT model because it is process-based, which means it is more suitable for simulating scenarios with different water management strategies than statistical or data-based hydrological models. The ABM runs on an annual timestep and provides information regarding the reservoir management decisions of the agents and the area agents decide to irrigate to the SWAT model. The SWAT model simulates the hydrology system for the following year.

The SWAT model produces output files giving each agent's ratio of cultivated area and crop yield, the amount of water stored and released from each dam daily, and the amount of water flowing from each sub-basin. This output from SWAT is then input into the ABM, where the agents use this information to make decisions. The data exchange between the two models continues until the end of the simulation (Khan *et al.*, 2017).

In contrast, Lin *et al.* (2022) and Hyun *et al.* (2019) combined their ABMs with calibrated RW models. Lin *et al.* (2022) developed a Python package called Py-RAMID, which they used to achieve the two-way coupling between the YAKRW and the ABMs. The ABMs provide the YAKRW model with a ratio that the YAKRW model would use to adjust the mean annual diversion. The YAKRW would provide the ABMs with the river discharge data.

Similarly, Hyun *et al.* (2019) coupled their ABM with a RW model. They used the data management interface tool to transfer data between RW and the ABM. The ABM provides each agent's irrigation area and diversions to the RW model, which provides streamflow data and the water level in the Navajo Reservoir.

3.4.6 Validation

Validation is crucial as it allows researchers to check if a model works correctly. Researchers in the studies reviewed have used two approaches in validating ABMs. One of these techniques is discussing how the model works with stakeholders who give feedback regarding where it works incorrectly and how it should work (Farolfi *et al.*, 2010). The other approach compares simulated values with observed/historical values (Khan *et al.*, 2017, Becu *et al.*, 2003, Lin *et al.*, 2022).

Both Farolfi *et al.* (2010) and Gurung *et al.* (2006) followed the ComMod methodology and involved stakeholders in validating their models. Farolfi *et al.* (2010) validated the KatAWARE model by discussing it with the stakeholders. When the researchers presented the KatAWARE V0, the stakeholders suggested multiple changes, some of which could be considered validations. One of the changes the stakeholders proposed was that the agents should be able to use the ecological reserve in the event of a drought. The authors incorporated the changes in KatAWARE V1.

In contrast, instead of discussing the Limbukha model with stakeholders as a way of validating the model, Gurung *et al.* (2006) took a different approach. The authors first developed an RPG version of the model, and the researchers let the stakeholders play the RPG for six timesteps. The stakeholders gave feedback regarding the rules of the game, and the researchers developed the computerised version of the model, which was the Limbukha model. The authors validated the Limbukha model by comparing its results with the RPG's. The researchers could not directly compare the values because the stakeholders only played the RPG for six timesteps. Instead, the authors compared the general patterns in the output of the RPG and the computerised model. The computerised model ran 30 simulations, each of which used 20 timesteps. They found that the average results of rice and potato plots and unused water were mostly consistent with the RPG's results. However, there were some differences. One of the differences was that the results of the computerised model showed that potatoes were not grown in some years, but the RPG results showed that farmers cultivated potatoes each year. The authors attributed this difference to the market price and rainfall pattern used in making decisions in the computerised model.

Khan *et al.* (2017) used surveys and compared the observed streamflow values at various points in the computerised model to observed values. They also compared the amount of hydropower generated by different agents with the observed amount generated. Similarly, Lin *et al.* (2022) validated their models by comparing the annual irrigation diversions generated by their model with historical irrigation diversions. The authors found that the coupled ABMs (Coupled-YAKRW and Coupled-YAKRW w/o S) closely matched the historical irrigation diversions.

Similarly, Becu *et al.* (2003) used the cropping pattern and average yields in validating CATCHSCAPE. After running the simulation 20 times, they found that the hectarage of the different cultivated crops matched that observed using remote sensing with an accuracy of 80%. The researchers compared the average yield simulated by the model with the observed yield and

found the model to be 70% accurate. In addition, the rise of wealthy farmers in the CATCHSCAPE model matched the reality. Still, the authors admitted that the model was less realistic in simulating the worsening economic position of poor farmers.

3.5 Chapter summary

AB modelling has been used in multiple studies in various contexts. In particular, this modelling technique was used to model the usage of natural resources, especially water, with high success. Although hydrologic models can be used to model water use in catchments, they do not explicitly represent the human impacts on the systems. Bennett *et al.* (2019) noted that the next step in their study was to incorporate AB modelling. The use of ABMs coupled with hydrological models provided realistic outputs.

However, there are challenges associated with developing ABMs. Some challenges include the need for accurate input data, detailed documentation and validation, and potential errors in model development. To overcome these challenges, AB modelling must be iterative, have stakeholder engagement, and have thorough validation. Model assumptions and uncertainties need to be carefully considered.

4

Methodology and Model Design

Chapter 2 suggested that developing an ABM with close interaction with KBV stakeholders could help improve the region's sharing and management of water resources. Such a study has never been conducted in the KBV; hence, this study set out to develop a tool for water sharing and management in the KBV.

As described in Section 1.4, this study aimed to ascertain the extent to which an ABM could be useful in modelling the KBV catchment area and simulating climate/usage scenarios. This chapter describes the research methodology for the study, including research design, stakeholder interaction, and data collection methods, resulting in the conceptual model.

4.1 Methodology

This study utilised the ComMod methodology (Barreteau *et al.*, 2004) as described in Section 3.2.4.1. The data collection methods used were stakeholder workshops and surveys, enabling qualitative and quantitative data collection.

4.1.1 Participatory modelling approach

As explained in Section 1.1, the KBV region is subject to water scarcity, resulting in user conflict and disregard for ecological water requirements. One of the objectives of this study was to develop an ABM through collaboration with the farmers and other stakeholders in the KBV region; therefore, a participatory modelling approach called ComMod was used in the study. As

described in Section 3.2.4.1, ComMod is an iterative and participatory methodology researchers use to build ABMs to discuss natural resource sharing among stakeholders (Barreteau *et al.*, 2003).

Multiple factors led to the choice of ComMod for this study. These were:

- The need for stakeholder engagement: ComMod is participatory, and stakeholders are involved at multiple stages of the modelling process.
- High complexity of the KBV catchment: ComMod allows researchers to understand the system while considering the stakeholders' multiple perspectives of the system.
- Co-creating a water management plan: The ComMod process can be used in collaborative decision-making with stakeholders, as demonstrated in the study by Gurung *et al.* (2006).
- Enhancing credibility: The study would require stakeholders to trust the results from the study for them to commit to any management strategies that would result from the study. Because ComMod involves the stakeholders at multiple stages of the modelling process, the stakeholders should have greater trust in the model than if the stakeholders were less involved.

As discussed in Section 3.4.1, ComMod has been used in multiple studies to engage stakeholders to discuss natural resource sharing with considerable success (Becu *et al.*, 2003, Farolfi *et al.*, 2010, Gurung *et al.*, 2006).

However, the method has some drawbacks, including the need for skilled facilitation, availability and commitment of stakeholders. The method is both time and resource-intensive. To mitigate these problems, a professional facilitator assisted during workshops. One of the reasons the study site was chosen was that most stakeholders in the region were keen to participate in the process (Gwapedza *et al.*, 2024). Unlike Farolfi *et al.* (2010), who performed two iterations, we carried out one iteration of the ComMod cycle due to time and resource constraints.

4.1.2 Stakeholder workshops

This section describes the three workshops held in the KBV.

The first workshop took place in May 2022 to carry out the ARDI process, an essential process in ComMod as described in Section 3.2.4.1. This process resulted in the stakeholders creating a shared representation of the KBV catchment. In addition, interactions with the stakeholders provided data that could be used to develop the ABM.

The next workshop was held in November 2022. During the workshop, a conceptual ABM was presented for correction and approval by the stakeholders. A visual presentation was given to the stakeholders that explained the various input data the model would require. In addition, the presentation showed how the model would work through several hypothetical scenarios. Some suggestions for changes were received, but overall, the model was considered an accurate representation. At the end of the workshop, the participants were given survey questionnaires with questions relating to how the individual farmers used the shared water supply.

The final workshop took place in November 2023. Various simulation scenarios and results were discussed with the stakeholders. The workshop aimed to show the stakeholders that the KBV ABM accurately reflected the KBV catchment and to obtain feedback. In addition, the stakeholders provided suggestions for additional simulation scenarios that they wished to see results of.

4.1.3 The ARDI process

The ARDI process described in Section 3.2.4.2 was followed in the first workshop. However, the participants were split into two groups, one identifying actors and resources and the other discussing the dynamics in the catchment. The main research question acted as the anchor in the discussions.

Multiple actors were noted in the identification of the actors stage. Some of the direct actors were farmers, labourers and eco-tourism operators. Some indirect stakeholders were the government, retailers, and the Water User Association (WUA). The resources that the stakeholders mentioned included soil, water, and biodiversity. Some of the dynamics that the stakeholders raised were irrigation, job creation, mining and water abstraction.

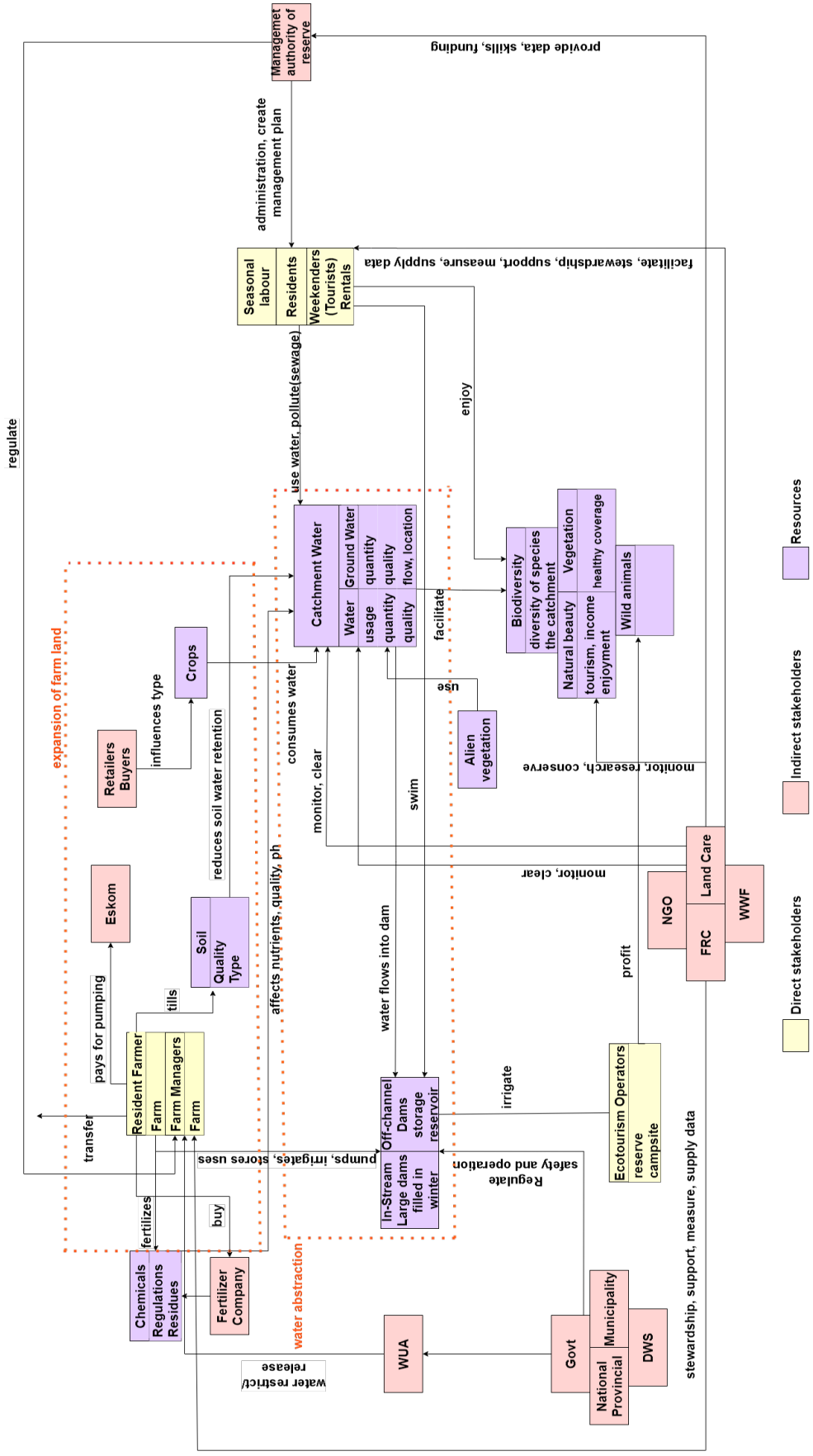

Figure 4.1: Interactions diagram created from the ARDI process in the KBV catchment.

Stakeholders were also asked to provide interactions between identified actors and resources and between two actors. Some of the interactions identified were the usage of water by crops and other vegetation, the pumping of water by farmers from the river into dams, and the tilling of the soil by farmers.

Figure 4.1 shows the interaction diagram created at the end of the ARDI process. The chart shows the actors, resources and interactions the stakeholders raised during the ARDI workshop. In this figure, Eskom is the electricity provider, and DWS is the Department of Water and Sanitation. NGO denotes non-governmental organisations such as the Freshwater Research Centre (FRC) and the World Wide Fund for Nature (WWF). Residents are people who live in the catchment, and Weekenders are people who have property in the catchment but do not reside permanently in the catchment.

The image shows the high level of complexity in the catchment. Because the research question was about how the stakeholders could use water more equitably and sustainably, only the components directly related to the problem were prioritised. The workshop facilitator guided the discussions to focus on the equitable and sustainable use of water. This was explained to the participants, and they accepted the simplification.

4.1.4 Survey about farming practices

A survey of farmer strategies and practices was carried out in the study. A questionnaire was given to stakeholders at the second workshop, and the responses from stakeholders were used as input data for Farm agents. We shared the survey with 10 participants and received responses from six participants.

4.1.4.1 Questionnaire design

The questionnaire had four sections: water abstraction, crop decisions, irrigation strategy and plans for the future. A copy of the questionnaire is given in Appendix A.

The water abstraction section included questions about the farmers' surface and groundwater usage. Information was sought about pumps, such as the pumping rate and location of each

pump, and dams, such as dam capacities, whether a dam is in-stream or off-stream and the percentage level at which farmers would start pumping water into the dams. Answers to questions in this section were required to understand the water storage capacity of each farm, how the dams were filled, the rate at which the farmers could fill the dams and when the farmers would fill their dams.

The section on cropping decisions included questions about how farmers decide whether to grow vegetable crops and the hectarage of each cultivated crop type. The questionnaire included these questions because crop types and hectarage are the main factors determining a farm's water requirements. Knowing how farmers decide when to grow vegetable crops was also important.

The irrigation strategy part of the questionnaire contained questions about the irrigation infrastructure available to each farmer, how farmers prioritised crops when irrigating in a period of water shortage, the volume of water used for irrigation during different months and the water sources. Irrigation equipment determines the efficiency of irrigation and thus affects the volume of water used for irrigation. There was a need to know how the farmers prioritised crops when irrigating during a water shortage, as this information would determine how the agents in the KBV ABM behaved in times of inadequate water supply. The question about the volume used for irrigation was important for improving the calculation of the water demand of crops in the KBV ABM.

The plans for the future section had questions about potential changes the farmers considered making. These included the construction of new dams, expanding or reducing the irrigated land under cultivation, and cultivating different crops. Answers to these questions would be used to inform possible future scenarios.

4.1.4.2 Summary of survey responses

Relevant information obtained from the survey responses is discussed in this section.

The catchment has multiple properties, with farms dominating. Properties not used for farming use water for domestic purposes only, and the water used for this purpose is insignificant when compared to that used for irrigation; therefore, these properties were not included in the KBV ABM.

Category	Responses Summary
Dam Information	
Number of farms with dams	3
Dam capacity (m^3)	Range: 17 000 - 720 000
Dam type	Mostly in-stream, some off-stream
Percentage of water required to start pumping	20% to 50%
Pumps	
Pumping rate (m^3/h)	Range: 40 to 280
Number of farms using pumps	3
Filling of dams with groundwater	
Use of groundwater to fill dams	Only in emergencies (1 farm)
Dependence on upstream releases	
Dependence on upstream releases	2 farms dependent
Water release for other farmers	
Release water upon request from other farmers	Not common
Requesting water from other farmers	
Requesting water from upstream farms	In dry summer months (1 farm)
Boreholes	
Pumping rate (boreholes, m^3/h)	Range: 10 to 30
Crop Hectarage	
Crop types	Citrus (oranges, lemons), deciduous (apples, nectarines, etc.)
Hectarage range (ha)	1.7 to 53
Soil Moisture Monitoring	
Use of soil moisture data for irrigation	All respondents
Irrigation Type	
Irrigation type	Micro-spray (all farms)
Irrigation Strategy with Limited Water	
Irrigation strategy	Allocate water by crop importance and growth stage
Crop Priorities	
High-priority crops	Citrus and apples
No irrigation in winter	All farms
Future Plans	
Future irrigation plans	New pipelines, drip irrigation, dam construction

Table 4.1: Summary of survey responses from farms regarding irrigation practices, water management, and future plans.

Table 4.1 shows on overall table of the survey results. Most farms within the catchment operate dams for irrigation purposes, with a mix of off-stream and in-stream designs. The survey responses indicate that in-stream dams are the most common type. Dam capacities vary significantly between farms, ranging from 17 000 m^3 on one farm to 720 000 m^3 on another. One farm reported that groundwater is only used to fill dams during extreme water shortages, while the other farms rely solely on surface water or upstream releases.

The variety of crops cultivated across the farms is diverse. The survey responses show the presence of both citrus crops such as oranges and lemons, and deciduous crops like apples, nectarines, pears, and peaches. Additionally, grass pastures were reported on some farms, used for grazing. The hectarage of cultivated farm lands displays significant variation, from as small as 1.7 ha up to a sizable 53 ha. This range demonstrates the differing scales of operation among the farms in the catchment.

In terms of irrigation practices, all farms reported using micro-spray systems for watering their crops. This uniformity in irrigation technique may indicate a shared understanding of its efficiency under current water resource constraints. Each farm also uses soil moisture monitoring systems, which are essential for scheduling irrigation events. These sensors help farmers optimize water use, ensuring that crops receive the necessary amount of water while preventing wastage.

The survey revealed that farms adopt varied strategies for water allocation during periods of scarcity. Each farm allocates irrigation water based on multiple factors, primarily the economic value of the crops and their current growth stages. High-priority crops tend to receive a larger share of water compared to lower-priority crops. This strategic allocation ensures that the most valuable crops are protected during water shortages. Crop prioritization also differs among farms: one farm ranked oranges as its top priority, while another gave precedence to apples. Farms with larger hectarages generally assigned their more extensive crop areas to high-priority crops. Importantly, all farms reported that they cease irrigation during the winter months (from May to September), reflecting both the seasonal water availability and reduced crop demands.

Regarding future plans, most farmers indicated intentions to improve their irrigation infrastructure. A common goal among the farms is to install new irrigation pipelines, while some farmers are considering switching to more water-efficient drip irrigation systems. This shift would potentially increase irrigation efficiency, especially under limited water availability. One farm planned

to construct new dams to increase storage capacity, while another expressed the intention to expand the area under cultivation, signaling ongoing investment in agricultural production.

4.1.4.3 Ethical considerations

We obtained ethics approval from the Rhodes University Ethics Committee for administering the survey (approval number 2022-5900-7264). To satisfy the ethics requirements, all participants were required to sign consent forms giving details about the study.

Anonymity could not be guaranteed during workshops or the survey process as workshops were collaborative, and survey responses had to be linked to individual farms for use as input for the ABM. However, confidentiality was maintained as the survey data was available only to the research team members. Additionally, scenario results were presented during the third workshop using identification codes instead of actual farm names.

4.1.5 Data sources

The study used data obtained from the surveys to satisfy the input needs of the ABM. Another data source used in the study was the Cape Farm Mapper (CFM) WCDoA (2023) developed by the Western Cape Department of Agriculture (WCDoA), which provided data regarding farm boundaries, crop type and hectarage. Figure 4.2 shows a screenshot from the CFM 3 website showing a farm and its crop fields bounded by the purple rectangle. Clicking the *Calculate Zonal Statistics* button results in the website providing the total hectarage of each crop type in the bounded region. We repeated this process to obtain crop hectares for those farms for which we did not have survey results. This was done for 6 farms which had 154 fields.

We obtained A-Pan evapotranspiration and crop factors data from the 1990 Surface Water Resources of South Africa Study (WR90) (Pitman *et al.*, 1998). Dam capacities were obtained through personal communication with Oliphant (2021), a South African National Space Agency (SANSA) representative.

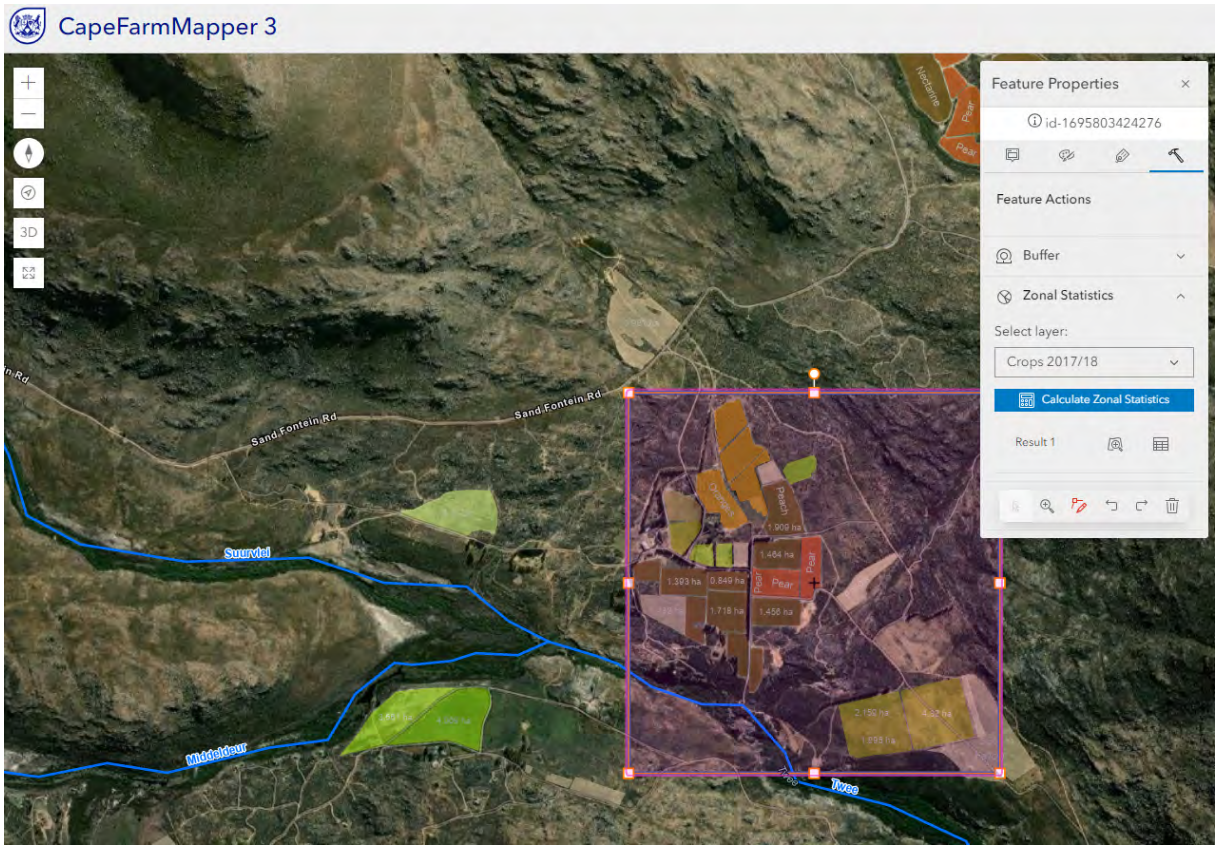

Figure 4.2: Extraction of crop hectarage for a farm – taken from WCDoA (2023)

4.1.6 Limitations in applying the methodology

Although ComMod is an effective methodology for developing ABMs with stakeholder collaboration, it has some drawbacks, including conflicts among stakeholders and the availability and commitment of stakeholders. The method is also time and resource-intensive. In addition, of the 11 questionnaires sent to farmers, only five responses were received. Moreover, some of the completed questionnaires had missing answers.

Another challenge was communicating model results to stakeholders in the third workshop because the results had to be easy to understand but still informative, and the model results for each individual farm could not be shown directly due to ethical considerations.

Various mitigation measures were used to combat these problems. The problem of stakeholder conflicts was mitigated by hiring a professional facilitator to assist during the workshops. One of the reasons the catchment E21H was chosen for this study was that most stakeholders in the region were keen to participate in the process (Gwapedza *et al.*, 2024). This meant that most of

the stakeholders in the catchment participated in the study. The issues of absent and incomplete questionnaires were solved using other data sources as explained in Section 4.1.5. Finally, simplified diagrams and identification codes were used instead of farm names to communicate model results in the final workshop. The identification codes were related to the position of the farms in the catchment, e.g., *UP-1*, *UP-2* for upstream farms and *D-1*, *D-2* for downstream farms.

The problem of time and resource constraints was solved by performing a single iteration of the ComMod cycle. This contrasts with the study by Farolfi *et al.* (2010), where two iterations were performed. Although we performed one iteration, we held several workshops (described in Section 4.1.2), which allowed us to interact with the stakeholders at various stages of the modelling process.

4.2 Model design

As described in Section 3.2.3.2, one of the steps in developing an ABM is creating a conceptual model (Loper, 2015). This section describes the conceptual model using algorithms and class and activity diagrams. The section provides information such as the types of agents represented in the model, their attributes, and activities.

4.2.1 High-level model overview

Figure 4.3 shows a high-level view of the model components and their main interactions. The ABM gets streamflow and rainfall input from a SWAT hydrological model developed by another researcher working under the same project, namely, Water Research Commission (WRC) Project Number C2020/2021-00607 (Mabohlo, 2023). The SWAT model was setup using default parameters, however, parameters associated with groundwater contribution to the stream were modified according to the modeller's understanding of catchment's physical characteristics in order to better match the flows observed during the dry period. Like Farolfi and Bonte (2005) and Khan *et al.* (2017), we used rainfall and streamflow data from a hydrological model in contrast to Gurung *et al.* (2006) whose model generated rainfall which could either be normal or low and then used the rainfall status in determining the amount of water available to farmers. We did not use this approach because, although it is simpler, it is less realistic than using data

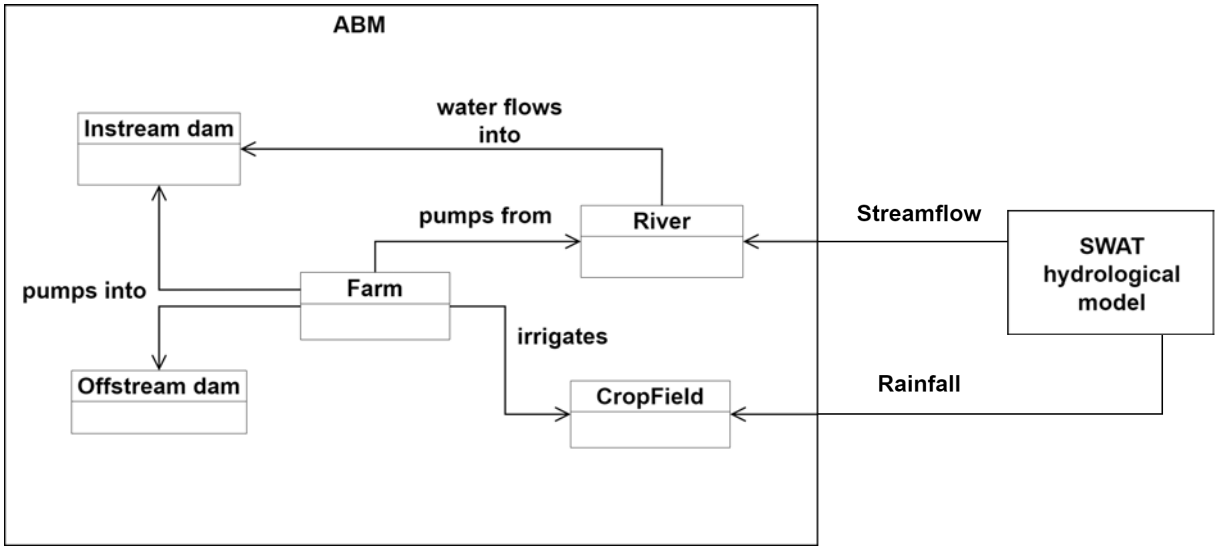

Figure 4.3: One-way coupling between the KBV ABM and the SWAT hydrological model

from a hydrological model. In addition, because SWAT is a process-based hydrological model, it reflects variations in the hydrology of catchments, making it suitable for linking with ABMs (Khan *et al.*, 2017). The one-way coupling was implemented in such a way that all water is accounted for and water usage upstream influences the volume of water available downstream. Details on the linkage of SWAT and the KBV ABM are given in Section 4.2.3.2.

The KBV ABM comprises four main entities: the river segments, farms, dams and crop fields.

4.2.2 Assumptions

Through the literature survey and from personal discussions with Barreteau (2023), whose research focuses on AB modelling and hydrology, the following assumptions were used in developing the conceptual model:

- 70% of total rainfall is considered the effective rainfall available to crops. This was adopted from the CROPWAT model, which can calculate effective rainfall using a fixed percentage with losses ranging from 0.1 to 0.3 (Smith, 1992).
- Irrigation for pasture and vegetable crops requires 20% more water because it uses sprinkler irrigation, which is less efficient and can have an efficiency of only 80% (Eisenhauer *et al.*, 2021b).

- All the water supplied during the irrigation of fruit trees is made available to the trees because they use highly efficient micro-spray irrigation, which has an efficiency of 90% (Eisenhauer *et al.*, 2021b).
- In the model, only surface water is used for irrigation. Groundwater is not considered in the ABM.
- Since the ABM does not consider groundwater, return flows are not represented.
- Water transfers from E21H to E21G are not represented in the conceptual model because no data about transfers between these regions was available.
- Water use by alien vegetation was not considered in the model.
- There is no economic component in the model; thus, no cost/benefit information can be provided.

4.2.3 Types of agents

The KBV ABM has multiple agents that behave similarly to the real-world entities in the catchment, namely Farm, RiverSegment, Dam, CropField and WUA agents. This section describes how the real-world entities that exist in the KBV catchment are represented in the conceptual model.

4.2.3.1 Farm agent

The KBV catchment has multiple farms. Each farm has several fields, and farmers cultivate different crops. The crops include apples, pears, oranges, and cabbages. Most farms have one or more dams that are used for irrigation. The conceptual model represents the farm and farmer as a single agent, namely, the Farm agent. The Farm agent decides how much irrigation water is supplied to different CropField agents, when to pump water to fill dams, and the hectarage of vegetable crops to cultivate.

4.2.3.2 RiverSegment agent

The conceptual model divides the KBV river system into 33 RiverSegment agents. Each RiverSegment receives water from its upstream RiverSegment and provides water to its downstream RiverSegment. If a RiverSegment feeds water into an in-stream dam, the RiverSegment does not allow water to go to the downstream RiverSegment until the dam is full and overflowing. The volume of water entering the in-stream dam is equivalent to the volume of water exiting the RiverSegment, as provided by the flow data from the SWAT model.

Although the RiverSegment network is a simplified form of the stream network from the hydrological model, all the water is accounted for. In-stream dams and farm boundaries were the main factors that determined where each RiverSegment would start and end. Figure 4.4 shows a portion of the catchment. The thin, light blue lines are the river channels defined by the hydrological model whose IDs are the black numbers, the grey areas are farms with the large bold letters being the farm IDs, and the thick lines are the RiverSegment agents. Light blue polygons are dams.

In Figure 4.4, RiverSegment 43 starts where RiverSegment 60 ends and as shown by the diagram, RiverSegment 60 is connected to an in-stream dam. The position where RiverSegment 43 ends coincides with the boundaries of Farm A and B. The hydrological model's channel flows are subtracted to determine the volume of water generated by streams on the land around a RiverSegment. For example, RiverSegment 96 has an upstream channel 101 and a downstream channel 95 (located under RiverSegment 94). The water flowing out of channel 101 is subtracted from the water flowing into channel 95. The result is the amount of water generated by the streams on the land surrounding the RiverSegment.

4.2.3.3 Dam agent

Most farms in the KBV catchment have in-stream or off-stream dams used for irrigation, with a few farms irrigating directly from the river. In-stream dams are situated in the river and must be full before water can flow downstream. Farmers pump water from the river into dams when they drop to a given threshold. In the conceptual model, we represent both in-stream and off-stream dams using Dam agents. Each in-stream Dam agent is connected to a RiverSegment agent from which it obtains water.

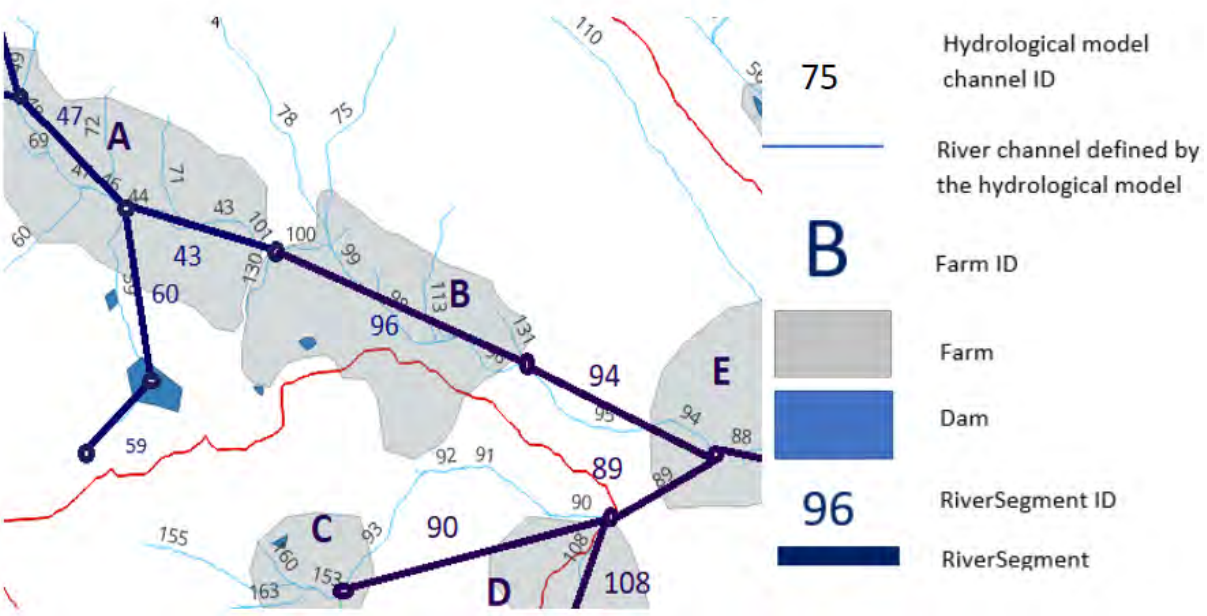

Figure 4.4: Design of part of the RiverSegment network

4.2.3.4 CropField agent

The conceptual model represents each farm's crop fields with CropField agents. Each CropField agent has a weekly irrigation water demand that the Farm agent needs to provide. We calculate the crop's irrigation water demand by considering weekly rainfall and the weekly evapotranspiration demand of the CropField agent. The agent also has fieldArea and cultivatedArea attributes. The latter is used for vegetable crops and changes from season to season depending on water availability.

4.2.3.5 Water User Association (WUA) agent

The `WUA` agent calculates the EWR flow at the catchment outlet and checks if the flow at the outlet is below the EWR. This is the only responsibility of the WUA in the base model. More complexity was added to the agent, as described in Chapter 5, to execute future simulations in which the WUA controls a shared dam.

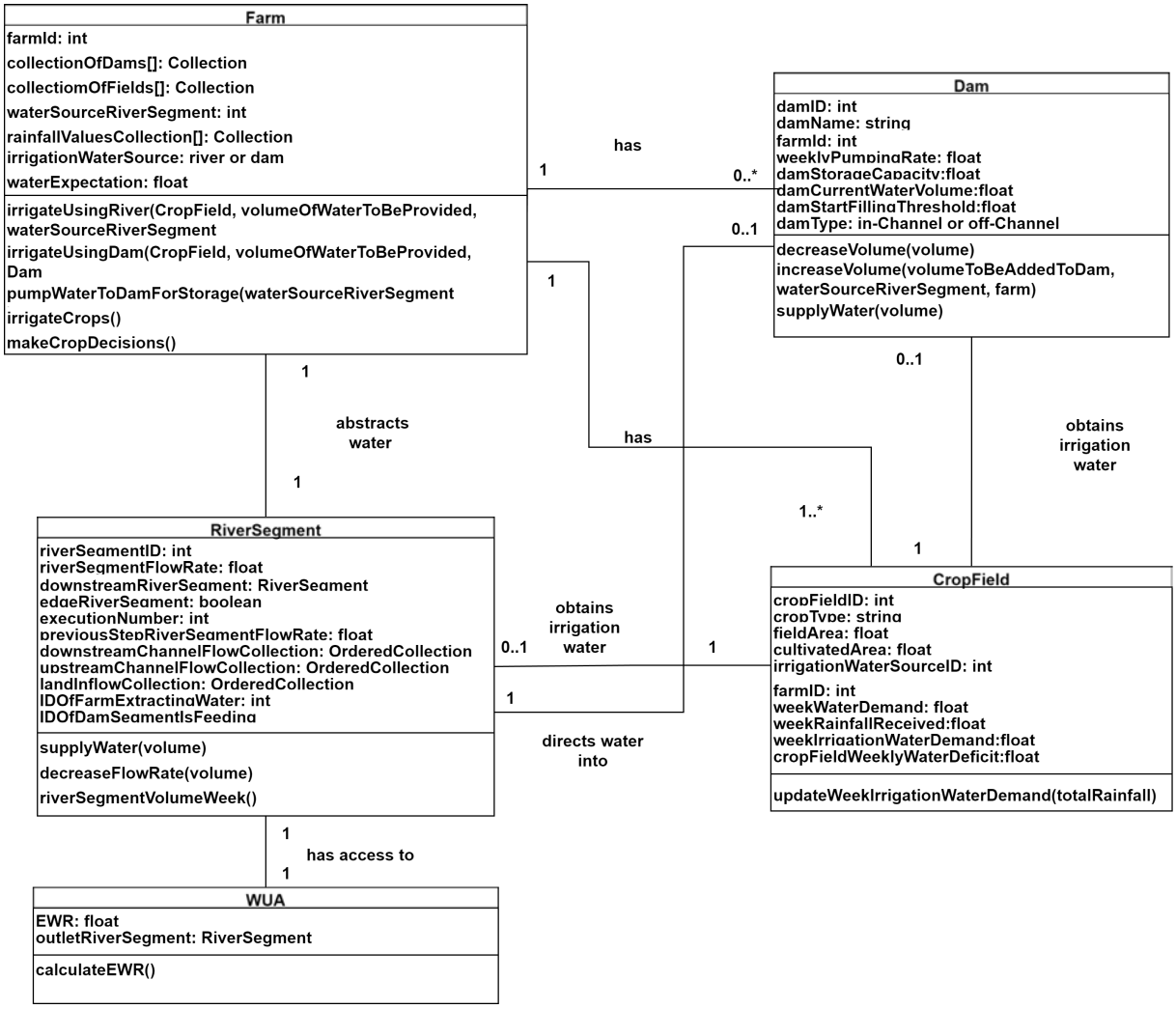

Figure 4.5: Class diagram of the conceptual model. It shows the agents in the conceptual model and how they are linked. The agents include the Farm, RiverSegment and Dam agents.

4.2.4 Structure of the conceptual model

The structure of the conceptual model can be described by highlighting the relationships between the agents and the overall scheduling of the model.

4.2.4.1 Conceptual model class diagram

Figure 4.5 shows the class diagram of the conceptual model. Each Farm has zero or multiple Dams. A Farm has one or more CropField agents, and a Farm has one RiverSegment from which it pumps water. Each CropField obtains irrigation water from either a Dam or a RiverSegment.

Algorithm 1 High-level overview of how the model operates at each timestep

```
for All the RiverSegments in order of execution number do
    if RiverSegment has a Farm pumping water then
        Execute the Farm;
    end if
    if RiverSegment is connected to an in-stream Dam then
        Ensure the in-stream Dam is full before routing water to the downstream RiverSegment;
    else
        Route water to the downstream RiverSegment;
    end if
end for
WUA calculates EWR
WUA warns if flow at the outlet is less than EWR
```

It is assumed that growers of the same crops have a similar abstraction schedule and irrigation technique. Some RiverSegment agents direct water into in-stream Dam agents.

4.2.4.2 Scheduling

Algorithm 1 shows how the conceptual model operates at each timestep. The operating sequence of the agents is determined by the execution timing of the RiverSegment agents. Each RiverSegment has an executionNumber attribute, which the model uses to control the order of execution of the RiverSegment agents. If a RiverSegment being executed has a Farm that obtains water from the segment, the Farm is executed. If the RiverSegment is connected to an in-stream Dam, the RiverSegment routes its water to the Dam until the Dam is full. The amount of water left is then routed to the downstream RiverSegment. This process is repeated for all RiverSegment agents in the model. After all the RiverSegments have run, the WUA calculates the EWR using the natural flow rate at the catchment outlet (i.e. the flow rate that would have occurred at the outlet if there were no human activities) and compares the EWR with the outlet RiverSegment agent's flow rate.

Figure 4.6 shows another representation of the model scheduling at each timestep or *Tick*. *R1*, *R2*, and *R3* are RiverSegments. At each tick, water is routed from upstream to downstream as shown by the arrows linking the RiverSegment agents. *F2a* and *F2b* are Farms agents obtaining water from *R2*. *F2a* is using the water for irrigation whilist *F2b* is using the water to fill dams. The *Output* from each RiverSegment is given by:

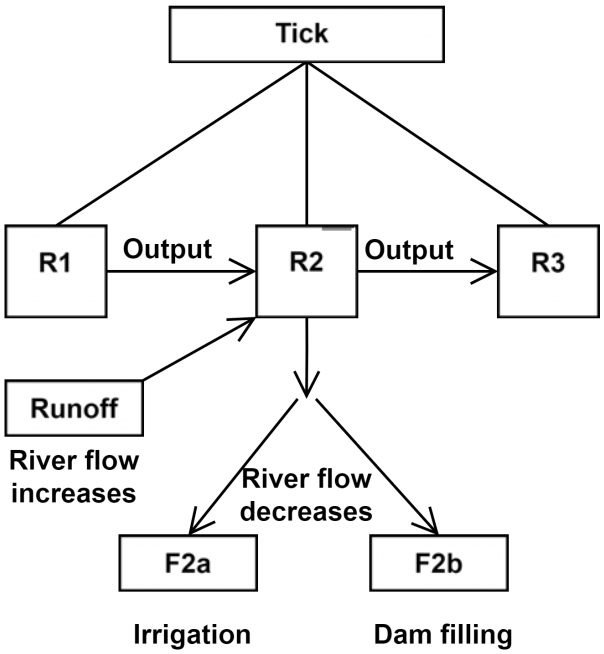

Figure 4.6: Model processes at each timestep.

$$Output = Input\ flow + Runoff - Farmer\ use \tag{4.1}$$

where *Output* is water flowing out of a RiverSegment, *Input flow* is water entering a RiverSegment, *Runoff* is water flowing into a RiverSegment from the surrounding land, and *Farmer use* is the water used by farmers for either irrigation or dam filling.

4.2.5 Farm activities

The main activities farmers perform in the conceptual model are irrigation and filling of dams (weekly) and planting vegetable crops (once per season).

Algorithm 2 describes the behaviour of a Farm agent at each timestep. At the beginning of the season, the Farm makes crop decisions, which involve determining the hectarage of vegetable crops to cultivate. This decision is based on the volume available in storage and the rainfall expectation. The fields in which crops are cultivated do not change. If the Farm has dams, it pumps water into the dams from the river. The Farm then checks the volume of water either in the river or in its dams. Depending on the volume of water available, the Farm can provide

Algorithm 2 How Farm agents behave at each timestep

```
if Timestep is the start of a new season then
    Farm makes crop decisions;
end if
if Farm has dams then
    Farm pumps water to dams;
end if
Farm checks if the irrigation water sources have enough water to irrigate fully;
if The irrigation water sources have enough water then
    Provide 100% of the required irrigation volume;
else
    Use crop priorities to determine the fraction of irrigation demand to provide;
end if
```

either 100% or a lower percentage of the irrigation demand to the CropField agents. In situations where there is a shortage, the highest priority crops get 100% of their water demand. If there is water left, the second most important crops get 80% of their water demand. This process is repeated with lower fractions for lower priority crops until there is no water left.

4.2.5.1 Irrigation

Since irrigation is the primary water usage in the KBV catchment, the water usage represented in the model is irrigation. The factors determining the water volume used for irrigation are the crop type, water demand, hectarage of the CropField agents, and the irrigation schedule.

Crop water demand

In the conceptual model, the water demand for crops is determined using the ET-WB method described in Section 2.6.3.2. A-pan evaporation and crop factor values for the KBV region were obtained from the WR90 study (Pitman *et al.*, 1998). Crop factors are similar to K_c as given in Equation 2.2, which is the ratio of ET_c to ET_0.

The crops grown in the KBV were divided into four categories: citrus, deciduous, onions, and pasture. Each class has crop factors for each month, while each month has A-pan evaporation values. Table 4.2 shows the A-pan evaporation for each month and each crop category's crop factor values per month.

Table 4.2: A-pan evaporation and crop factors for each month for citrus deciduous, onions and pasture crops – taken from (Pitman *et al.*, 1998)

Month	Oct	Nov	Dec	Jan	Feb	March	April	May	June	July	Aug	Sept
A-pan Evaporation (mm)	183.91	256.24	314.58	320.09	264.09	244.15	149.76	84.85	55.58	54.09	75.73	118.15
Crop factors												
Citrus	0.45	0.45	0.50	0.55	0.60	0.65	0.70	0.65	0.60	0.45	0.45	0.45
Deciduous	0.24	0.27	0.36	0.45	0.57	0.48	0.20	0.20	0.20	0.20	0.20	0.20
Onions	0.70	0.80	0.00	0.00	0.00	0.00	0.15	0.32	0.40	0.57	0.66	0.70
Pasture	0.70	0.00	0.80	0.80	0.80	0.80	0.70	0.60	0.50	0.50	0.50	0.60

Table 4.2 shows the monthly A-pan evaporation. In addition, the table also shows the crop factors for each month for each of the four crop categories.

To obtain each crop's monthly gross water requirement, the A-pan evaporation is multiplied by the crop factor. The resulting gross water requirement is the water depth the crop requires during that month. Because the model operates at a weekly timestep, each crop type's monthly gross water requirements are disaggregated into weekly values by dividing them by the number of weeks in each month. The effective rainfall is subtracted from the weekly gross water demand to obtain the weekly irrigation water demand. For pastures and onions, the irrigation water requirement is increased by 20% because sprinkler irrigation is used to irrigate crops instead of micro-spray irrigation (which is more efficient), meaning more irrigation water is applied.

Irrigation scheduling

The irrigation scheduling depends on crop water demand, water availability, and crop priority. Each Farm agent has attributes determining the percentage of water demand a Farm provides to a CropField agent when there is a water shortage. Each CropField agent has summerPriority and winterPriority attributes. The Farm agent uses these attributes to prioritise crops during irrigation.

Figure 4.7 shows a Farm agent's steps when irrigating during each timestep. At the beginning of the season, a Farm sorts its CropFields agents according to crop priorities. The Farm agent then calculates the total irrigation demand of all its CropField agents. The Farm agent compares the total irrigation water demand to the volume of water available in storage or the river. A Farm agent has an attribute irrigationWaterSource that specifies the source of its irrigation water, which can be either a dam or a river. If the available water equals or exceeds the irrigation water demand, the Farm agent provides the CropField agents with 100% of their water demand.

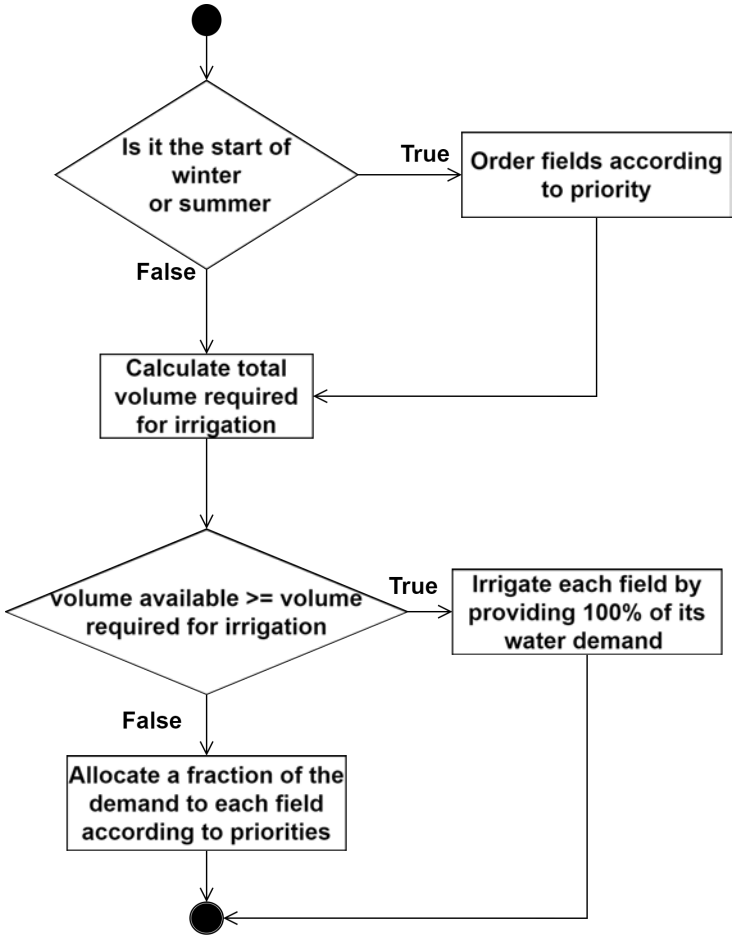

Figure 4.7: High-level activity diagram of the irrigation process.

Suppose the total water demand exceeds the available water volume, then the Farm agent irrigates the CropField agents in the order of importance with the volume determined by the CropField agent's priority.

4.2.5.2 Cultivation of vegetable crops

Some farmers in the catchment cultivate vegetable crops. The hectarage of the vegetable crops is determined at the beginning of each season based on the previous year's rainfall and the volume of water they have in storage.

Similar to Becu *et al.* (2003), who provided a water expectation attribute for the Farmer agents to use in determining the types of crops they would cultivate, in this conceptual model, the Farm agents use an attribute called waterExpectation in combination with the total volume of water in storage to determine the hectarage of vegetable crops. The waterExpectation attribute keeps

Algorithm 3 How Farm agents determine the hectarage of vegetable crops to cultivate

if water expectation $\geq$ water required **then**
  fraction to be cultivated = 1;
else if Farm number of dams = 0 **then**
  $fraction\ to\ be\ cultivated = \frac{water\ expectation}{water\ required}$;
else
  $fraction\ to\ be\ cultivated = \frac{total\ volume\ in\ storage}{total\ capacity}$;
end if

track of the previous year's rainfall, which the Farm agents use to predict the following year's rainfall. The conceptual model has a parameter rainfallThresholdForFullVagetableCropCultivation, which the Farm agents use in determining the hectarage of the vegetable crops to cultivate.

The hectarage of the vegetable crops is calculated according to the steps shown in Algorithm 3. At the beginning of a new season, each Farm determines the fraction of the field area to cultivate vegetable crops by checking if the waterExpectation is greater than or equal to the threshold amount required for full vegetable cultivation. If the condition is satisfied, there will be full cultivation of vegetable crops, i.e., each CropField allocated to vegetables will have a cultivatedArea equal to its fieldArea. If the amount of water expected is less than that required for full cultivation and the Farm has no dams, the fraction of the field area for vegetable cultivation will be the ratio of the water expected to the required water. If the Farm has a Dam, the fraction will be the ratio of the Farm agent's total volume of water stored to total dam capacity.

4.2.6 Implementation of the model

The Cormas framework, developed by the French Agricultural Research Centre for International Development (CIRAD), was used to implement the KBV ABM for multiple reasons, which were:

- Cormas has been successfully used in similar studies (Farolfi *et al.*, 2010, Becu *et al.*, 2003, Gurung *et al.*, 2006).
- As stated in Section 4.2, this study was undertaken as part of the WRC Project Number C2020/2021-00607 with The National Research Institute for Agriculture, Food and the Environment (INRAe) as a project partner. Given that researchers from the organisation were part of the project and had contributed to the development of Cormas, it meant that technical support would be readily available.

- As described in Section 3.2.4.4, Cormas has an interactive diagram feature which would enhance the collaboration capabilities of an ABM built with the tool.

The full implementation of the KBV ABM was conducted in a series of iterations, building from a basic model to a more complex one. Verification was performed at various stages of implementation, and validation was performed after all the model components had been added. The steps followed in implementing the KBV ABM are given below:

1. Development of the river network. The river network was implemented by connecting the RiverSegment agents. Flow in the river network was verified by comparing the flow rate from SWAT with that from the KBV ABM at various points in the catchment to determine if they matched. The river network was refined multiple times to ensure that all the streamflows generated by SWAT were included in the KBV ABM.

2. Addition of crops and irrigation. Crops were added as CropField agents whose water and irrigation demands were calculated as explained in Section 4.2.5.1. At this stage, all farms directly used the river for irrigation.

3. Addition of in-stream and off-stream dams. The dams were added as Dam agents, and farms with dams could now use dams for irrigation. The water balance was verified, i.e., we checked whether the water input into the model was equal to the sum of water used for irrigation, in storage and leaving the catchment. This check was important as it allowed us to determine if the KBV ABM was losing or gaining water through errors in the implementation.

4. Validation of the model. The model was validated using survey information, workshops, and consultation with the KBV catchment coordinator (Theron, 2023). In particular, the coordinator checked the simulation results from 1 October 2017 to 30 September 2020 to see if the water shortages matched what he had witnessed in the catchment during that period. We also presented some of the historical model results to stakeholders at the third workshop.

4.2.7 Using the model to simulate future scenarios

On completion of the successful validation of the model, various simulation scenarios were executed. Some of the scenarios explored, including those involving shared dams and increased dam capacities, were suggested by stakeholders, and these scenarios are described in detail in Chapter 6. The following simulation scenarios were designed:

- Moderate climate change scenario. This scenario simulates water usage between 2025 and 2030 using the current land use but with streamflow and rainfall data generated by SWAT under moderate carbon emissions predicted rainfall and temperature.
- Extreme climate change scenario. This scenario simulates water usage between 2025 and 2030 using the current land use, but streamflow and rainfall data generated by SWAT using high carbon emissions predicted rainfall and temperature.
- Increase in hectarage and climate change scenario. This simulation scenario is similar to the moderate climate change scenario. However, the difference is that upstream farmers increase the hectarage of their main crops by 20%.
- Shared dam, 10% increase in dam capacities and moderate climate change. This scenario is also similar to the moderate climate change scenario, with the difference being the addition of a shared dam and increased dam capacities. Downstream farms have access to the shared dam with a volume of 1 094 627 m^3, and the other farms increase their dam capacities by 10%. The WUA agent determines the volume each Farm can use from the shared dam, and the agent also releases water for the EWR.
- Shared dam, 20% increase in dam capacities and moderate climate change. This is similar to the previous scenario except that the shared dam had a volume of 2 189 25 m^3, and farms without access to it increased their dam capacities by 20%.
- Water releases by two big dams and moderate climate change. This scenario is similar to the moderate climate change scenario, but the difference is that farms owning the two big dams in the catchment release water during the dry season.

These simulation scenarios were chosen through the survey results and stakeholder workshops. Section 4.1 showed that some farmers planned to increase hectarage and add new dams. Ad-

ditionally, the stakeholder workshops showed that farmers were interested in determining how climate change would affect the catchment.

4.2.7.1 Future climate projections

To explore future scenarios using the KBV ABM, future climate predictions of rainfall and temperature were input into SWAT to provide rainfall and streamflow to the KBV ABM. For this purpose, the Rossby Center Regional Climate Atmospheric Model version 4 (RCA4) datasets were used (Kupiainen *et al.*, 2011). The RCA4 is the Swedish Meteorological and Hydrological Institute (SMHI) Regional Climate Models (RCM) that participated in downscaling Global Climate Models (GCMs) outputs generated for future periods under the Coordinated Regional Downscaling Experiments (CORDEX) (Kisembe *et al.*, 2018, Prein *et al.*, 2015).

Datasets from two Representative Concentration Pathways (RCPs), 4.5 and 8.5, were used to represent the future assessment period from 2025 to 2060. RCP 4.5 was used to represent a future of an intermediate scenario of carbon emissions, while RCP 8.5 was used to represent an increased scenario of carbon emissions (Gumbo and Kapangaziwiri, 2021, Kisembe *et al.*, 2018). The choice of RCA4 model, i.e. model AFR-44_MPI-ESM-LR_r1i1p1_RCA4_v1, driven by Max Planck Institute for Meteorology with a horizontal grid spacing of the simulation of 0.44 degrees (about 50 km) (Giorgetta *et al.*, 2013), was based on information in studies by Endris *et al.* (2015) and Gumbo *et al.* (2021). The studies showed that this version of the RCA4 model runs better than the RCA4 model when driven by other global climate models. These studies showed that this version of the RCA4 model successfully reproduces large-scale signals, such as the El Niño–Southern Oscillation, in both the historical and future periods over the Eastern and Southern Africa regions than the RCA4 model when driven by the other global climate models.

To capture the conditions of the KBV, bias correction followed the extracted station CORDEX data set. For this, the spreadsheet version (Linear Scaling bias correction (V.1.0) Microsoft Excel file) that applies the statistical downscaling method known as linear scaling bias correction (Shrestha *et al.*, 2016, Teutschbein and Seibert, 2012) was used. The downscaling is based on the average difference between the monthly observed time series and the historical run time series of GCM/RCM over the same period (Teutschbein and Seibert, 2012). These differences are then applied to simulated climate data to get bias-corrected climate variables, and for this study,

multiplicative correction, which is preferable for variables like precipitation, vapour pressure, and solar radiation (Shrestha *et al.*, 2016), was used to correct historical data and generate correction factors. The future time series or the projected data was bias-corrected with the same correction factor generated from the correction of the historical data (Teutschbein and Seibert, 2012).

The process followed to obtain future climate values (as explained above) was applied to all parts of the umbrella project under which this research falls (Gwapedza *et al.*, 2024).

The results of this process showed that from 2025 to 2030, RCP 4.5 had higher temperatures and lower rainfall than RCP 8.5. However, for the period 2025 to 2060, RCP 4.5 had lower temperatures and higher rainfall than RCP 8.5.

4.2.7.2 Calculating the EWR

Paxton *et al.* (2016) developed a tool to monitor EWR called STandardised REserve Analysis and Monitoring tool (STREAM), which they applied in the KBV. STREAM calculates monthly EWR using two flow duration curves tables. To determine the EWR for each month, the percentile of the natural (i.e. with no human impact) flow volume has to be identified in the Natural Flow Duration curves table. The corresponding flow volume is then identified in the Total EWR Duration curves table (the EWR). The river flow volume is then compared to the EWR; if the river flow is less than the EWR at any time under consideration, the EWR would not have been met.

This process is quite complex. We consulted Paxton (2023), an aquatic ecologist at Freshwater Research Centre, on calculating the EWR more simply. He suggested that we use the Total EWR Duration curves with the 20^{th}, 50^{th} and 90^{th} percentiles representing the dry, average and wet conditions, respectively (Paxton *et al.*, 2016). The KBV ABM uses this approach. We converted the monthly flow volumes into weekly flow rates and stored them in a table. When determining if the EWR is met in the KBV ABM, the natural flow rate is compared to the three possible EWR values for that week. The closest value to the natural river flow rate is taken as the EWR value.

4.3 Chapter summary

This chapter described the methodology followed in this research and the model design. The study used the ComMod methodology, and the reasons for this choice were explained, which include the need for stakeholder engagement, the high complexity of the catchment and the need to enhance the credibility of the model. The chapter explained the data collection methods, including workshops and surveys. A description of the workshops, survey and survey results was given. Details of the model design were given by first highlighting the agents representing real-world entities in the KBV catchment. The chapter described how each of the agents behaves and how the agents interact. The conceptual model described in this chapter formed the basis of the implemented version of the model described in Chapter 4. Finally, the chapter outlined the steps taken to implement the model, the verification and validation processes carried out, and a description of the simulation scenarios explored using the model.

5

Model Implementation, Verification and Validation

This chapter describes the implementation process of the KBV ABM. It explains how features of the Cormas framework were used in creating the model, how verification and validation were performed, and how indicators and visualisations were incorporated into the model. The chapter also discusses implementation challenges and how we overcame them. All listings in this chapter are given in pseudocode, as Smalltalk is not a commonly used language. However, the Smalltalk code is available in Appendix B. In addition, code for the KBV ABM can be accessed on the project's GitHub repository[1]. Note that `typewriter` font is used to depict actual identifiers and method names in the Smalltalk code.

5.1 Structure of the base model

Figure 5.1 shows the class diagram of the KBV ABM, which is similar to that shown in Figure 4.5, but with the inclusion of Cormas superclasses from which the agents inherit, highlighted in orange.

As described in Section 3.2.4.4, Cormas has three types of classes which can be used when designing ABMs, namely the spatial, social and passive classes, which are explained below.

[1] https://github.com/Rody10/KBV_ABM

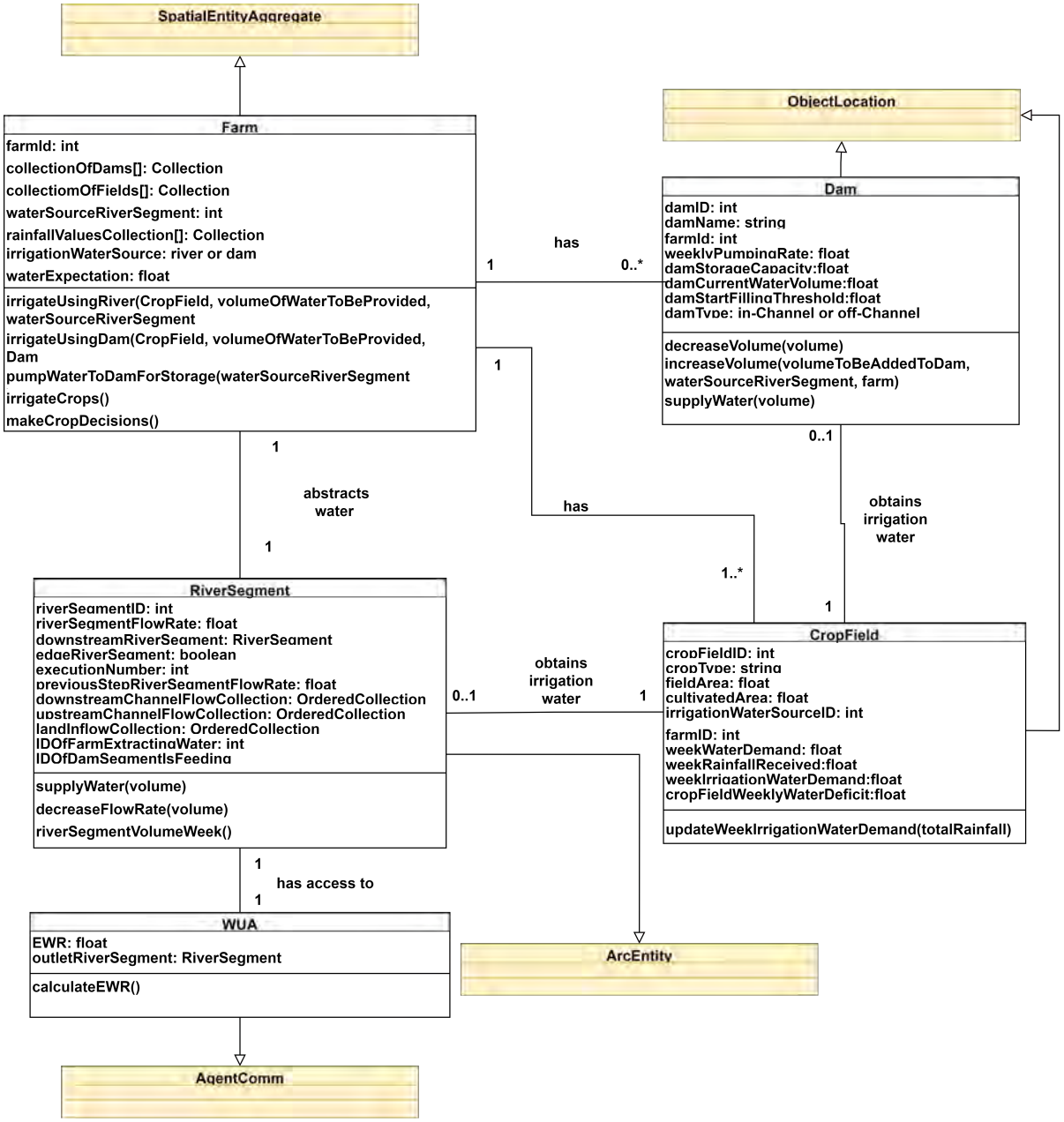

Figure 5.1: Class diagram showing the structure of the model and the superclasses of the agents

5.1.1 Spatial entities

The model uses a grid of 88 x 114 cells, each representing an area of approximately 3.8 ha. The `Farm` agent is a spatial entity that inherits from the `SpatialEntityAggregate` class, used for creating entities made up of connected cells. As explained in Section 4.2.3, the `Farm` agent acts as both the farm and the farmer in the ABM.

5.1.2 Social entities

The base model has one social entity, which is the WUA. This agent inherits from the `AgentComm` class, which is a class used to define entities that can communicate. The WUA is defined as a social agent because it enables scenarios that involve shared dams, as explained in Chapter 5. However, in the base model, the WUA's sole responsibility is calculating EWR at the catchment outlet.

5.1.3 Passive entities

In Cormas, a passive entity is a simple entity, such as a land cover or a message (Bommel *et al.*, 2016). The KBV ABM has three entities in this category, namely, `Dam`, `CropField` and `RiverSegment` agents. The superclass for both the `Dam` and the `CropField` entities is the `ObjectLocation` class, which is used to create entities that require a specific location in the environment. The `RiverSegment` agents' superclass is the `ArcEntity`. More details regarding the development of the river network and use of the `ArcEntity` are given in the next section.

5.2 Implementation of the river network

Unlike Farolfi *et al.* (2010), who used sub-catchments (implemented as spatial entities) to represent the hydrological system, the KBV ABM uses `RiverSegment` agents as described in Section 4.2.3.

The `ArcEntity`, which is meant for implementing canals, rivers and roads, is defined by two nodes called the `startNode` and the `endNode`. All the `ArcEntities` combine to form a specific network.

In the KBV ABM, the `ArcEntity` is specialised to represent river sections implemented as `RiverSegment` agents. The `startNode` depicts the upstream start of the segment, while `endNode` depicts the downstream end of the segment. Both nodes are defined using the cell coordinates corresponding with the `origin` and `destination` attributes of a `RiverSegment`.

```
createRiverNetwork()
    coordinatesCollection = createCoordinatesCollection()
    pairsOfCoordinatesCollection = createPairsOfCoordinatesCollection(coordinatesCollection)
    createNetworkOfArcs(RiverSegment, pairsOfCoordinatesCollection)
    setValuesForEntities(RiverSegment, 'channel_routing_table.csv')
```

Listing 5.1: Pseudocode for the method to create a river network

```
initTwee()
    [...]
    for each rs in theRiverSegments:
        rs.upstreamChannelFlowCollection = initializeChannelFlowCollections(rs.riverSegmentID,
     2)
    for each rs in theRiverSegments:
        rs.downstreamChannelFlowCollection = initializeChannelFlowCollections(rs.
    riverSegmentID, 3)
    for each rs in theRiverSegments:
        rs.initializeLandInflowCollection()
    initializeDownstreamRiverSegments()
    orderRiverSegments()
    [...]
```

Listing 5.2: Pseudocode for the initialisation of channel flow collections and ordering of `theRiverSegments` collection

5.2.1 Initialisation of the river network

Listing 5.1 shows the pseudocode for the `createRiverNetwork()` method, which is responsible for setting up the `RiverSegment` network. The method first creates a collection of coordinates using the `createCoordinatesCollection()` method, which reads an external file containing the origin and destination coordinates of all the `RiverSegment` agents. The `createPairsOfCoordinatesCollection()` method uses the `coordinatesCollection` to create another collection, called the `pairsOfCoordinatesCollection`, which contains pairs of coordinates defining the origin and destination of `RiverSegment` entities. The new collection is used by the `createNetworkOfArcs()` method to create the river network. The attributes of each `RiverSegment` are then defined using the Cormas method `setValuesForEntities()`, which takes the entity type and an external CSV file with attribute values as parameters.

In Cormas, when an agent is instantiated, the agent is added to a collection called `theAgentClassName`. All the `RiverSegment` agents are added to the `theRiverSegments` collection.

Listing 5.2 shows how the collections that store channel flows are initialised and the `theRiverSegments` collection is ordered according to `executionNumber`. As described in Section 4.2.3.2, the model accounts for all water by associating each `RiverSegment` with its corresponding upstream and downstream channel from SWAT. The `upstreamChannelFlowCollection` and

```
step(t)
    for each riverSegmentBeingExecuted in theRiverSegments:
        landInflow = riverSegmentBeingExecuted.weeklyInflow(t * 7 - 6)
        if landInflow > 0:
            riverSegmentBeingExecuted.riverSegmentFlowRate += landInflow
        if riverSegmentBeingExecuted.farmExtractingWaterFromRiverSegment != nil:
            farmToBeExecuted = riverSegmentBeingExecuted.farmExtractingWaterFromRiverSegment
            farmToBeExecuted.step(t, riverSegmentBeingExecuted, crop_lookup_table)
        if riverSegmentBeingExecuted.damSegmentIsFeeding == nil:
            routeWaterForRiverSegmentWithoutInstreamDam(riverSegmentBeingExecuted)
        else:
            routeWaterForRiverSegmentWithInstreamDam(riverSegmentBeingExecuted)
    for each WUA in theWUAs:
        WUA.step()
```

Listing 5.3: Pseudocode for the main method executed by the scheduler at each timestep

`downstreamChannelFlowCollection` are attributes that each `RiverSegment` has, and they store daily flow values for the associated upstream and downstream channels from SWAT. The code loads both collections for each `RiverSegment` using data from external CSV files. The `landInflowCollection` for each `RiverSegment` is initialised using the difference between corresponding values in the `upstreamChannelFlowCollection` and `downstreamChannelFlowCollection`, which represents the volume of water flowing into the `RiverSegments` from the surrounding land on each day.

5.2.2 RiverSegment agent behaviour

This section describes how the `RiverSegment` agents behave, emphasising their ordered execution to allow the simulation of water flow in the KBV ABM.

The behaviour of `RiverSegment` agents is closely linked to scheduling in the model shown in Listing 5.3. As explained in Section 4.2.4.2, the model executes `RiverSegment` agents from upstream to downstream. The collection `theRiverSegments` is already ordered according to the `executionNumber`, and hence, the model executes the `RiverSegments` in the order they appear in the collection.

When executing a `RiverSegment` agent, the model first calculates the volume of water flowing into the `RiverSegment` from the surrounding land using the `weeklyInflow()` method, which calculates weekly inflows using the `landInflowCollection` collection. The `landInflow` increases the `RiverSegment` agent's flow rate. If the particular segment has a `Farm` pumping water from it, the `Farm` is executed, and the `Farm` agent's behaviour can reduce the

`RiverSegment` agent's flow rate. Lines 9 to 12 show that if a `RiverSegment` is connected to an in-stream dam, the `routeWaterForRiverSegmentWithInstreamDam()` method is executed, which results in water flowing into the in-stream dam until the dam is full before it is allowed to pass to the `downstreamRiverSegment` as explained in Section 4.2.3.3. If the `RiverSegment` is not connected to an in-stream dam, the `RiverSegment` agent's flow rate is then passed on to the `RiverSegment` agent's `downstreamRiverSegment` using the `routeWaterForRiverSegmentWithoutInstreamDam()` method.

For each timestep, this process is repeated for all `RiverSegment` agents in the `theRiverSegments` collection.

5.2.3 Verification of the river network

The river network was verified by running the model (without filling dams or irrigation) for one year and comparing the KBV ABM output with the SWAT model's output. The period that was chosen was 1 October 1997 to 30 September 1998.

Figures 5.2, 5.3 and 5.4 show graphs comparing the flows from SWAT and those from the KBV ABM for three sections of the catchment, namely, the upper, lower and catchment outlets, respectively. R^2 and NSE were adopted in determining the extent to which the KBV ABM's flows matched those from SWAT. It can be seen from all the graphs that flow from the SWAT model and the KBV ABM match. The R^2 value for all the graphs was 1, and the NSE value was 0.998. According to Ritter and Muñoz-Carpena (2013), a goodness-of-fit evaluation where the NSE is above 0.65 is acceptable, and those greater than 0.9 are very good. According to Ritter and Muñoz-Carpena (2013), a goodness-of-fit evaluation is considered acceptable when the NSE is above 0.65, and values greater than 0.9 indicate a very good fit. This shows that the KBV ABM correctly represented the river network in the SWAT model.

5.3 Implementation of Farm agents

The Farm agent was implemented as a spatial entity representing the attributes and behaviour of both the farms and farmers.

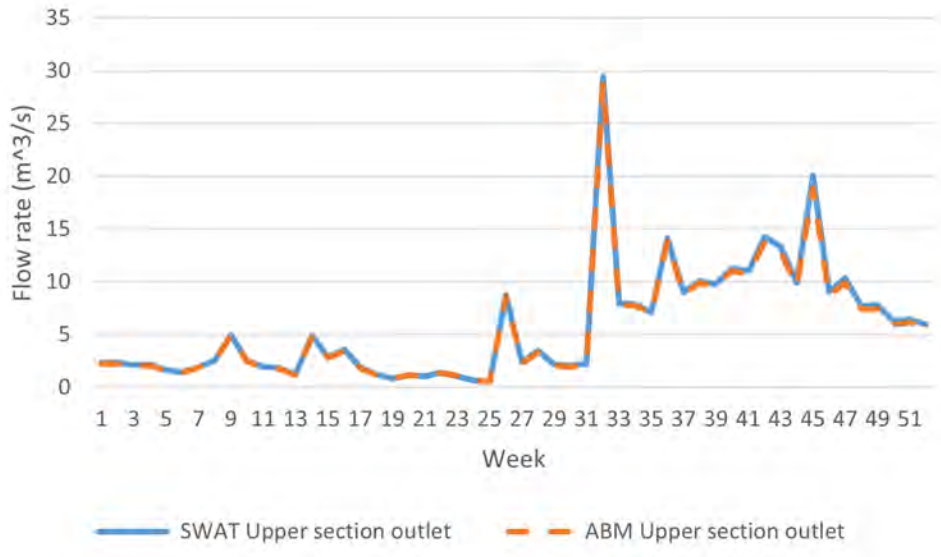

Figure 5.2: Graph showing a comparison of SWAT and the KBV ABM flows at the outlet of the catchment's upper section.

```
1  createFarms()
2      loadAttribute(farmID, 'Farms_200m.txt')
3      createFragmentedEntities(Farm, farmID)
4      fakeFarm = nil
5      for each f in theFarms:
6          if f.farmID == 0:
7              fakeFarm = f
8      fakeFarm.delete()
9      for each f in theFarms:
10         cellsCollection = f.getEpidermis()
11         f.farmID = cellsCollection.at(1).farmID
12     setValuesForEntities(Farm, 'farms_data.csv')
```

Listing 5.4: Pseudocode for the initialisation of `Farm` agents

5.3.1 Initialisation of Farm agents

The initialisation of `Farm` agents uses a raster file whose dimensions match the ABM's grid dimensions.

Listing 5.4 shows how the model initialises `Farm` agents. The method reads a raster file whose cell values are used to create the `Farm` agents using the `createFragmentedEntities()` method. All cells with the same `farmID` attribute belong to a specific `Farm`. Line 8 shows the deletion of a `fakeFarm` whose `FarmID` is 0 because the raster input file uses 0 for cells not part of any `Farm` agents. The method `setValuesForEntities()` initialises the attributes of each `Farm` agent using an external CSV file.

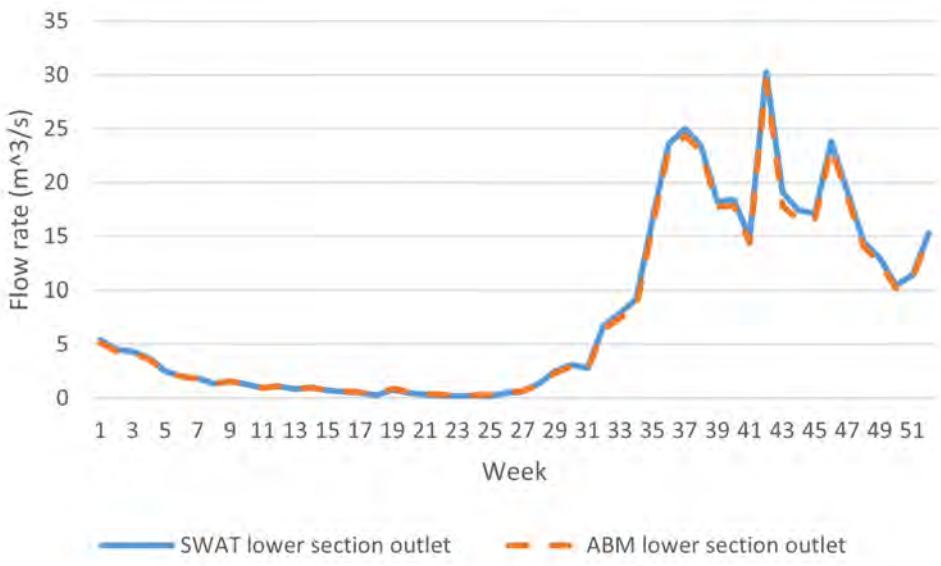

Figure 5.3: Graph showing a comparison of SWAT and the KBV ABM flows at the outlet of the catchment's lower section.

5.3.2 Farm agent's behaviour

This section describes the implementation of the `Farm` agent's behaviour, which includes the cultivation of vegetable crops, the filling of `Dam` agents and irrigation of `CropField` agents.

Listing 5.5 shows the `step()` method for `Farm` agents, which is executed at each timestep. A `Farm` first checks if it is the beginning of either winter or summer and, if so, orders the `CropField` agents in the `theCropFields` collection using the crop priorities attributes. If it is the beginning of a new season (1 April), a `Farm` executes the `makeCropDecisions()` method, where it determines the hectarage of vegetable crops to cultivate and plant the vegetable crops. A key method called by the `makeCropDecisions` method is the `calculateFractionOfVegetableHectarageToCultivate()` method, described by Algorithm 3.

After dealing with the planting of vegetable crops, a `Farm` agent pumps water to its dams and obtains rainfall for the week using the `weeklyRainfall()` method as shown in line 14 of Listing 5.5. This method works similarly to the `weeklyInflow()` method used by the model scheduler. Not all rainfall is available for crops; therefore, the rainfall is multiplied by 0.7 to give the `effectiveRainfall`. The `effectiveRainfall` is used to determine the irrigation demands for `CropField` agents, which has been described in Section 5.5.1. Lines 23 to 26 check if the `Farm` agent has access to enough water to meet the irrigation requirements of

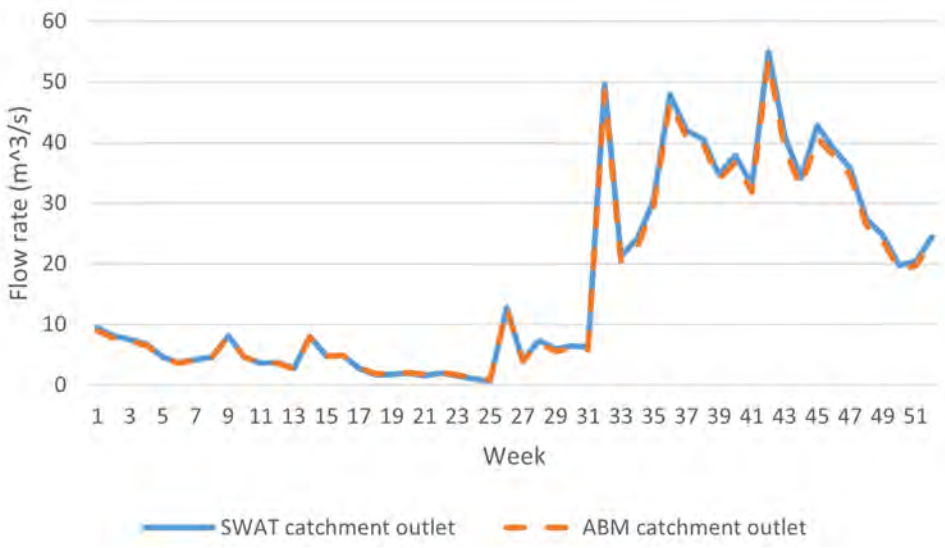

Figure 5.4: Graph showing a comparison of SWAT and the KBV ABM flows at the final outlet of the catchment.

its `CropField` agents. The `thereIsEnoughWater` variable holds a Boolean value signifying whether there is enough water to irrigate fully. After confirming that there is enough water for irrigation, the `irrigateCropsAfterSortingFields()` is executed.

The `irrigateCropsAfterSortingFields()` method iterates through each of the `CropField` agents associated with a `Farm` and irrigates them. A key determinant of the volume of water supplied to each `CropField` is the value of the `thereIsEnoughWater` attribute. If the value is `true`, a method called `irrigateWhenThereIsEnoughWater()` is used when irrigating, and if the value is `false`, the `irrigateWhenThereIsNotEnoughWater()` method is used.

Listings 5.6 and 5.7 show the `irrigateWhenThereIsEnoughWater()` and `irrigateWhenThereIsNotEnoughWater()` methods, respectively. Both methods determine the irrigation volume for a `CropField` agent but do so differently. Line 2 of Listing 5.6 shows that the volume of water provided for irrigation is the `CropField` agent's irrigation water demand. In contrast, Line 2 of Listing 5.7 shows that the volume of water provided for irrigation is obtained by multiplying a `CropField` agent's irrigation water demand by `fractionOfWaterDemandToBeProvided` whose value can range from 0.2 (for low priority `CropField` agents) to 1 (for high priority `CropField` agents).

Another difference between the methods is the use of the `irrigateHighPriorityCropUs-`

```
step(week, waterSourceRiverSegment, crop_lookup_table)
    [...]
    if beginningOfWinter:
        orderCropFields('winter')
    else:
        if beginningOfWaterYear:
            orderCropFields('summer')
            resetFarmAndCropFieldIndicators()
        else:
            beginningOfNewSeason || (week == 1):
                makeCropDecisions()
    pumpToDamsForStorage(waterSourceRiverSegment, WULVolume)
    updateTotalVolumeBeforeIrrigation()
    totalRainfall = weeklyRainfall(week * 7 - 6)
    effectiveRainfall = totalRainfall * 0.7
    for each field in collectionOfFields:
        field.updateWeekRainfallReceived(effectiveRainfall)
     for each field in collectionOfFields:
        field.updateWeekIrrigationWaterDemand(effectiveRainfall)
    updateRainfallDuringWeek()
    updateTotalFarmWaterDemand()
    updateWaterExpectation(effectiveRainfall)
    if irrigationWaterSource == 'dam':
        thereIsEnoughWater = checkIfDamsHaveEnoughWater()
    else:
        thereIsEnoughWater = checkIfRiverSegmentHasEnoughWater(waterSourceRiverSegment)
    irrigateCropsAfterSortingFields(season, WULVolume, waterSourceRiverSegment,
    effectiveRainfall, thereIsEnoughWater)
    updateTotalFarmDamWaterStorage()
```

Listing 5.5: Pseudocode for the method executed by each `Farm` agent at each timestep

`ingDams()` method. Line 3 of Listing 5.7 checks whether the priority of the `CropField` to be irrigated is 1 or 2. If the condition is satisfied and the `Farm` is using `Dam` agents for irrigation, the `irrigateHighPriorityCropUsingDams()` will be used to irrigate the `CropField`. The method allows water from multiple `Dam` agents to be used to irrigate high priority `CropField` agents if multiple `Dam` agents are available.

5.4 Implementation of Dam agents

Dams are implemented as passive objects, i.e., they do not have any active behaviour that executes at a timestep.

5.4.1 Initialisation of Dams

Listing 5.8 shows the method `createDams()` that initialises `Dam` agents. The method first uses a CSV file to create instances of `Dam` agents. It sets the attribute values of the agents and moves each of the `Dam` agents to a coordinate obtained from GIS data in the CSV file.

```
irrigateWhenThereIsEnoughWater(aField, waterSourceRiverSegment, damToBeUsedForIrrigation, WULVolume)
    volumeOfWaterToBeProvided = aField.weekIrrigationWaterDemand
    if irrigationWaterSource == 'dam':
        irrigationWaterProvided = volumeOfWaterToBeProvided
        irrigateUsingDam(aField, volumeOfWaterToBeProvided, damToBeUsedForIrrigation)
    else:
        irrigationWaterProvided = waterSourceRiverSegment.calculateVolumeOfWaterTheRiverSegmentCanProvide(volumeOfWaterToBeProvided, WULVolume, waterUsedDuringQuarterSoFar)
        irrigateUsingRiver(aField, irrigationWaterProvided, waterSourceRiverSegment)
    return irrigationWaterProvided
```

Listing 5.6: Pseudocode for the irrigateWhenThereIsEnoughWater() method

```
    irrigateWhenThereIsNotEnoughWater(aField, waterSourceRiverSegment, damToBeUsedForIrrigation, cropPriority, fractionOfWaterDemandToBeProvided)
    volumeOfWaterToBeProvided = aField.weekIrrigationWaterDemand * fractionOfWaterDemandToBeProvided
    if cropPriority == 1 || cropPriority == 2:
        if irrigationWaterSource == 'dam':
            irrigationWaterProvided = irrigateHighPriorityCropUsingDams(aField, volumeOfWaterToBeProvided)
        else:
            irrigationWaterProvided = waterSourceRiverSegment.calculateVolumeOfWaterTheRiverSegmentCanProvide(volumeOfWaterToBeProvided, WULVolume, waterUsedDuringQuarterSoFar)
            irrigateUsingRiver(aField, irrigationWaterProvided, waterSourceRiverSegment)
    [...]
    return irrigationWaterProvided
```

Listing 5.7: Pseudocode for the irrigateWhenThereIsNotEnoughWater() method

The `Dam` agent's possible behaviour is quite simple as it only involves storing water and making available water for irrigation. A `Dam` agent has attributes that enable this behaviour. These include `damStorageCapacity`, which is the maximum volume a `Dam` can store, `damCurrentWaterVolume` which is the volume of water in a `Dam` at a specific timestep and `damType` which can either be `in-stream` or `off-stream`.

5.5 Implementation of CropField agents

Like the `Dam` agent, the `CropField` agent is implemented as a passive object. The method that initialises `CropFields` is called `createFields()`, and it is similar to the `createDams` method. The only difference is that the two methods use different initialisation CSV files. To provide this passive behaviour, various attributes are needed for the `CropField` agent, including `cropType`, `cultivatedArea` and `irrigationWaterSourceID`.

```
createDams()
    createInstancesFromClass(Dam, 'dams.csv')
    setValuesForEntities(Dam, 'dams.csv')
    for each d in theDams:
        cellIndex = (d.cormasX asInteger + ((d.cormasY asInteger - 1) * self.gridSize.x)) asInteger
        d.isMovedTo: (self.theCells at: cellIndex)
```

Listing 5.8: Pseudocode for the initialisation of `Dam` agents

```
1  updateWeekIrrigationWaterDemand(effectiveRainfall)
2      weekNumber = currentSimulation.timeStep
3      fieldWaterDemandInMM = getCropWaterDemand(cropType, ((weekNumber - 1) \\ 52) + 1)
4      fieldWaterDemand = fieldWaterDemandInMM * 10 * cultivatedArea
5      if category == 'deciduous' || category == 'citrus':
6          fieldIrrigationWaterDemand = ((fieldWaterDemandInMM - effectiveRainfall)) * 10 * cultivatedArea
7          weekWaterDemand = fieldWaterDemand
8          weekIrrigationWaterDemand = fieldIrrigationWaterDemand
9      else
10         fieldIrrigationWaterDemand = (fieldWaterDemandInMM - effectiveRainfall) * 10 * cultivatedArea
11         adjustedIrrigationWaterDemand = fieldIrrigationWaterDemand + (fieldIrrigationWaterDemand * 0.2)
12         weekWaterDemand = fieldWaterDemand
13         weekIrrigationWaterDemand = adjustedIrrigationWaterDemand
```

Listing 5.9: Pseudocode for the updateWeekIrrigationWaterDemand() method

5.5.1 CropField agent's behaviour

A `CropField` agent's main behaviour is updating its irrigation water demand. Listing 5.9 shows the `updateWeekIrrigationWaterDemand()` which `CropField` agents use in determining their irrigation water demand.

Line 3 extracts the weekly water demand for the `CropField` using the `crop_lookup_table`. The `crop_lookup_table` is a nested dictionary whose outer key is the `cropType` and the inner key is the week number. The water demand values in the inner dictionary were obtained by multiplying the A-Pan evapotranspiration with crop factors for each month using Table 4.2. The values were then disaggregated by dividing the demand by the number of weeks in each month. A dictionary was chosen to hold this data as it allows fast access, and the values do not need to be modified as the model executes.

The resulting water demand is then converted to a volume to obtain the demand for the `CropField`. Line 5 checks if the `CropField` has fruit trees. If there are fruit trees, efficient irrigation is used, meaning the irrigation demand will be the difference between the water demand and the effective rainfall. However, if the `CropField` does not have fruit trees, meaning it has pasture or

vegetable crops and less efficient irrigation is used, the irrigation demand is increased by 0.2, as shown in line 11. This is how the irrigation efficiency assumption was implemented, as described in Section 4.2.2.

5.6 Scheduling

Scheduling of the model defines the order in which agents are executed. This was partly described in Section 5.2.2 as it relates to the behaviour of `RiverSegment` agents. This section expands on the scheduling of other agents.

Listing 5.3 line 6 checks if the `RiverSegment` being executed has a `Farm` that extracts water from the `RiverSegment`. If the condition is satisfied, the `Farm` agent is executed as shown in line 8. After the `Farm` agent has executed its behaviour, water is routed through the `RiverSegment` to either an in-stream `Dam` or the `downstreamRiverSegment` as described in Section 5.2.2. After all the `RiverSegment` agents have executed, the WUA calculates the EWR at the catchment outlet.

5.7 Verification of the water balance

Ensuring the model is not losing or gaining water due to errors is essential. The water balance was verified to check for any unexpected loss or gain of water. Verifying the water balance involves checking if the volume of water input into the model equals the sum of the water leaving the catchment, the volume of water used for irrigation and the volume of water in storage at the end of the simulation. We used a modified form of Equation 2.1 in Section 2.1:

$$\begin{aligned} &Streamflow\ input = \\ &Runoff + Water\ used\ for\ irrigation + \Delta Water\ in\ storage \end{aligned} \tag{5.1}$$

The reason for modifying the equation was that the KBV ABM does not consider all processes in Equation 2.1 such as evapotranspiration and change in soil moisture. Additionally, precipitation

in the KBV ABM is not used for irrigation and does not contribute to streamflow, as this is already considered in the SWAT model.

The water balance for the catchment was calculated to check if any such errors were present in the KBV ABM. The model was initialised using initialisation data for 2019 and run for one year without dams and irrigation, and the flow rate rate at the outlet was recorded. The model was then run again, including irrigation and dams. The dams started with zero volume to simplify the calculations. This time, the amount of water used for irrigation, the volume in storage at the end of the simulation, and the flow rate at the catchment outlet were recorded.

The flow rate obtained when running the model with no dams and irrigation was converted to a volume and compared to the sum of the volume of water leaving the catchment, the volume used for irrigation and the volume in storage at the last step of the simulation that included the use of dams and irrigation. The difference between these volumes should be zero. However, there was a small difference representing 1.213×10^{-6} % of the input volume caused by floating-point errors.

5.8 Indicators and visualisations

The KBV ABM tracks multiple indicators at different scales. Indicators include `RiverSegment` flow rate, water demand and deficit at a crop field, farm and catchment scale and volume in storage at the dam, farm and catchment scale.

Cormas allows a modeller to track attribute changes using *probes*, which are methods that return the values of attributes. To track indicators using probes, a modeller needs to select the *Notify observers when changed* option when creating the attribute that stores the value of the indicator of interest as shown in Figure 5.5. After this, the modeller must create the probe method, which simply returns the attribute value.

As an example, the probe method used to track the volume of water in a `Dam` simply returns the `Dam` agent's `damCurrentWaterVolume` attribute.

Visualisations are important to show the ABM dynamics. Cormas can be used to provide different visualisations. The framework provides line graphs for all probes, and a modeller can create other

Figure 5.5: Selection of the *Notify observers when changed* option

```
1 povFarmWaterStress
2   ↑self
3     povAttribute: #averageFarmWaterStress
4     min:0
5     max:1
6     color: ColorValue red
```

Listing 5.10: Method to visualise water stress at a farm level

visualisations using *pov* methods, which allow a model user to view different points of view in the simulation interface map.

Some pov methods used in the KBV ABM model are `povCropFieldWaterStress()` and `povFarmWaterStress()`. Stress is the ratio between the volume of water deficit and the volume of water needed. The values for stress range from zero to one, with zero meaning there was no deficit and one meaning there was no water.

Listing 5.10 shows the `povFarmWaterStress()` method used to visualise water stress for each `Farm`. Line 3 shows that the method calls a Cormas method called `povAttribute()` whose parameters are `attribute name`, `min` and `max` values of the attribute and `color`. The Cormas method is passed the parameters `averageFarmWaterStress`, 0 and 1 as the `min` and `max` values and `ColourValue red` as the `color`.

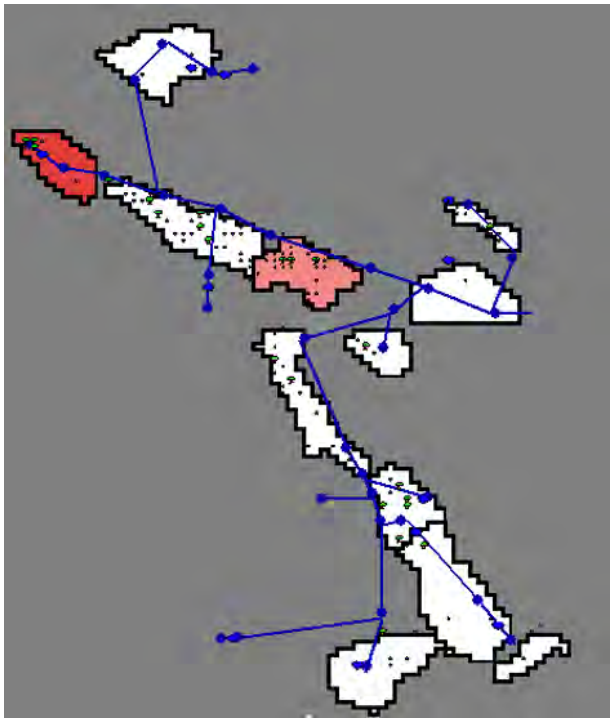

Figure 5.6: Visualisation produced by the `povAverageFarmWaterStress()` method

Figure 5.6 shows the output produced by the `povAverageFarmWaterStress()` pov method. It shows that for this timestep, two farms were stressed. The level of water stress is represented by the shade of red, with dark red representing higher stress than lighter red.

This type of visualisation is similar to the ones used in (Cuevas, 2020, Smajgl and Bohensky, 2013). Smajgl and Bohensky (2013) used this type of visualisation to show the levels of poverty and deforestation with different shades of red and green, respectively, while Cuevas (2020) used red and blue circles to represent infected and uninfected agents, respectively.

5.9 Implementation challenges and solutions

Multiple challenges were encountered when implementing the ABM KBV. This section describes the issues that arose and how these were solved.

The SWAT hydrological model outputs data as CSV files. If the file is edited with a tool such as Microsoft Excel, it converts the lowercase *e* in numbers that are in scientific notation to an uppercase `E`. When Cormas reads these values, it truncates the value from the *E* position. For

Channel routing table						River segments edges coordinates table			
riverSegmentID	downstreamRiverSegmentID	executionNumber	edgeRiverSegment	IDOfFarmExtractingWater	IDOfDamSegmentIsFeeding	firstX	firstY	secondX	secondY
20	21	1	TRUE	nil	1	33	16	28	17
21	18	2	FALSE	nil	0	28	17	22	12
18	49	3	FALSE	4	0	22	12	18	17
49	47	4	FALSE	nil	0	18	17	21	35
33	62	5	TRUE	nil	3	5	27	9	31
62	54	6	FALSE	9	0	9	31	14	32
54	47	7	FALSE	nil	0	14	32	21	35
47	43	8	FALSE	nil	0	21	35	28	37
59	60	9	TRUE	nil	4	27	53	27	48
60	43	10	FALSE	nil	0	27	48	28	37
43	96	11	FALSE	3	0	28	37	34	41
96	94	12	FALSE	7	0	34	41	46	46
94	86	13	FALSE	nil	0	46	46	53	49
284	242	14	TRUE	1	0	46	107	48	99
276	275	15	TRUE	nil	11	28	102	30	102
275	242	16	FALSE	nil	0	30	102	48	99
242	190	17	FALSE	nil	0	48	99	48	85
253	250	18	TRUE	nil	9	64	103	60	97
250	248	19	FALSE	nil	10	60	97	51	84
248	189	20	FALSE	8	0	51	84	48	85
190	189	21	FALSE	nil	0	48	85	47	81
191	189	22	TRUE	nil	0	40	81	47	81

Figure 5.7: Structure of the file used to design and make changes to the river network.

example, if the value is 1.23E+10, it becomes 1.23. To solve this problem, the string representation of the value being read is first converted into lowercase before conversion from string to number.

Another issue that was encountered was maintaining the order of the initialisation files used in initialising `RiverSegment` agents, which are the `river_segments_edges_coordinates.csv`, which has coordinates of the start and end nodes of each `RiverSegment` and the `channel_routing_table.csv`, which contains some attribute values for each `RiverSegment` such as `executionNumber` and `IDOfDamSegmentIsFeeding`, which is the ID of the in-stream `Dam` attached to a `RiverSegment`. Ideally, these input files should be combined; however, it was impossible to do so. This problem could result in `RiverSegments` having incorrect attribute values due to mistakes in the order of values in the initialising files. To solve this problem, a file containing data from both initialisation files was created.

Figure 5.7 shows the file structure. This file is not used directly by the KBV ABM but is supposed to be used by a model user when designing the river network or adding in-stream `Dams`. The model user first makes changes using this file before copying the changes to the initialisation files, thereby reducing the likelihood of errors occurring due to the wrong ordering of values in the initialisation files.

There are multiple points in the model where there is a need to access certain agents' instances. An example is when water flows from a `RiverSegment` to its `downstreamRiverSegment`. During the early stages of model development, `RiverSegment` agents did not have the `downstreamRiverSegment` attribute. Instead, they only had the `downstreamRiverSegmen-`

`tID` attribute, which meant at each timestep and for each `RiverSegment`, the model had to search `theRiverSegments` collection for a `RiverSegment` instance whose `RiverSegmentID` matched `downstreamRiverSegmentID` of the `RiverSegment` being executed. This was inefficient. To increase efficiency, the `downstreamRiverSegment` attribute, which stores a pointer to the `RiverSegment` whose ID matches the `downstreamRiverSegmentID`, was added to `RiverSegment` agents. The `downstreamRiverSegment` attribute is initialised during the initialisation of the model. This improved the execution speed of the model at the expense of additional memory and a slight increase in initialisation time. This approach is used multiple times in the model to improve execution speed.

5.10 Implementation decisions to support future expansion

Some implementation decisions were made to facilitate model expansion. These decisions included having quarterly water-use licences for each `Farm` and storing water demand for each crop type instead of for each crop category.

Although we did not obtain data regarding each farm's water-use licence, the model can easily be expanded to include this information. Each `Farm` agent has a water use licence attribute for each quarter. The agents check whether they exceed their allocated volumes before pumping water from the river. This is why the `pumpToDamsForStorage()` and `irrigateCropsAfterSortingFields()` methods have a `WULVolume` parameter. In the current model, the values of the water-use licence attributes have been set very high such that they do not influence model execution.

As explained in Section 4.2.5.1, the crops were divided into four categories because the data source we used for crop water demand had data at the level of the four crop categories. When implementing the `crop_lookup_table` dictionary, we decided to have each crop type as the outer key, which means we duplicated crop water demands of crops in the same category. We chose this because if a model user has water demands at the crop type level (not at the category level like in this study), it will be easy to update the model. The user would only need to update the `crop_lookup_table.csv` input file, which is used in initialising the `crop_lookup_table` dictionary.

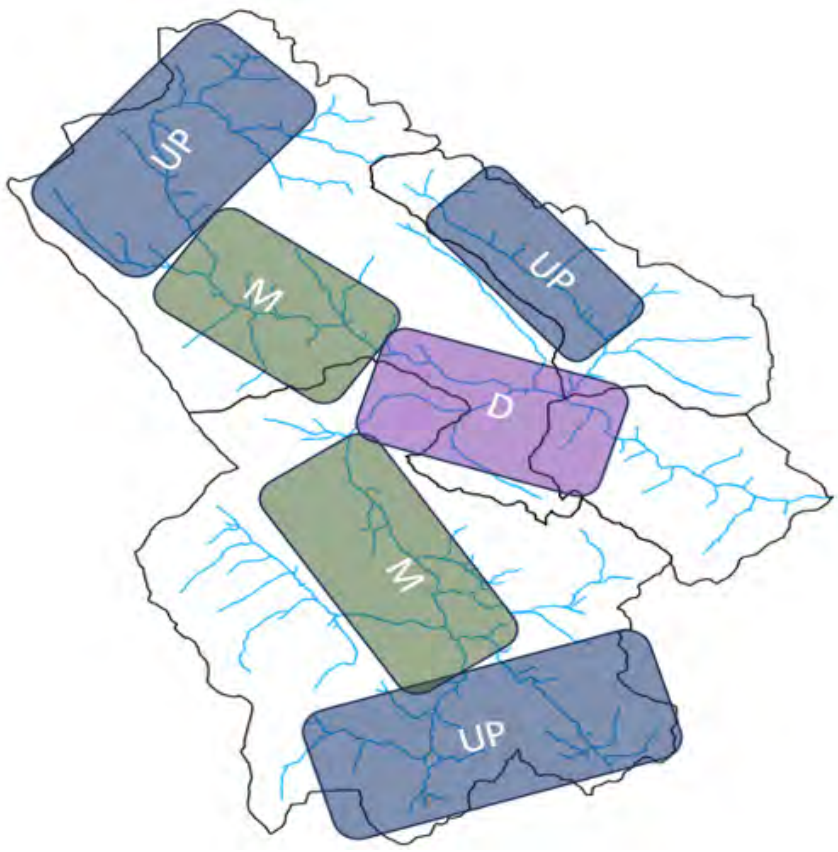

Figure 5.8: Map showing grouping of farms into upstream (UP), midstream (M) and downstream (D).

5.11 Validation

Similar to Farolfi *et al.* (2010) and Gurung *et al.* (2006), we validated the KBV ABM with input from stakeholders. Although no written historical data on the number of days with water shortages were available, stakeholders confirmed that the model outputs, such as water shortages and demand patterns, were consistent with their lived experiences on the farms during the simulated periods. This aligns with the approach used by Smajgl and Bohensky (2013), who validated the SimPasi model through expert consultation. Therefore, despite the scarcity of historical water usage data, the stakeholders' experiences provided a practical form of validation, particularly regarding the accuracy of water demand and shortages over time.

To maintain confidentiality during feedback-gathering sessions with the stakeholders, farms were grouped into different categories depending on their location in the catchment and assigned different codes, such as UP-1 for an upstream farm, M-1 for a midstream farm and D-1 for a downstream farm (see Figure 5.8). An upstream farm is defined as a farm with no other farm

upstream that uses the river water for irrigation purposes; downstream farms are farms close to the outlet, while midstream farms are the remaining farms.

5.11.1 Validation Test 1: Validation of water demand

This test aimed to determine if the water demand calculated by the KBV ABM was realistic using survey data. One of the questions in the stakeholder questionnaire was about the volume of water each farmer uses for irrigation when there is enough water per season. We received responses to this question from three farms, namely UP-2, M-3 and D-1. For this validation, the baseline model was executed for 52 timesteps from October 2019 to September 2020.

5.11.1.1 Data used

The test used current land-use data, rainfall and streamflow generated by the SWAT model from October 2019 to September 2020. The structure of the model was the same as that described in Chapter 3.

5.11.1.2 Results

The KBV ABM showed that the three farms had a total water demand of 1 212 305 m^3. However, data from the survey showed that the farms would have used 1 446 390 m^3. This means the KBV ABM's water demand was 234 085 m^3 lower than the demand reported in the survey.

To rectify this discrepancy, a parameter called `cropWaterDemandCorrectionFactor` was added to the model and its value was set to 1.2 because of the underestimation. The method for updating a `CropField` agent's water demand shown in Listing 5.9 was modified by multiplying the water demand obtained from the dictionary holding water demands by the `cropWaterDemandCorrectionFactor`.

5.11.2 Validation Test 2: Validation of water shortage experienced by farms

The test was run to determine if the water shortages experienced by farms were realistic. Obtaining exact water shortage values for each farm was impossible because there were no historical

records with this information. Therefore, we relied on feedback workshops with the farmers and sought confirmation from the catchment coordinator on how accurate the model was.

5.11.2.1 Data used

The test used current land-use data, rainfall and streamflow generated by the SWAT model from October 2017 to September 2020. The updated KBV ABM included the `cropWaterDemandCorrectionFactor` parameter implemented in Validation Test 1.

5.11.2.2 Results

Figure 5.9 shows the simulation results. The figure shows the average catchment water stress and the percentage each farm contributes to the catchment water stress. The water stress is the ratio of water deficit to water demand, meaning if water stress is zero, enough water is available, but if it is one, there is no available water. The average catchment water stress is the average water stress of all the farms in the catchment. We chose water stress to show some results because it allowed us to compare water availability for different farms more easily than using volumes directly, as the farms require different amounts of water.

Figure 5.9 shows that for each hydrological year (starting on 1 October and ending on 30 September), there was a higher water shortage during the summer months (December to March) compared to other periods. This is because, as explained in Section 1.1, the KBV gets most of its rainfall during winter, and there is little rainfall in summer. In addition, there is high water demand during this period. These two factors resulted in lower water availability during these months compared to other months.

Another aspect to note is the relatively high water stress in the catchment and the higher number of farms experiencing water shortage in the summer of 2018. This can be attributed to the drought experienced in the Western Cape from 2015 to 2018 (Archer *et al.*, 2019). There was lower-than-average rainfall, so there was not enough water for irrigation.

Figure 5.9 also shows that two farms had relatively higher water stress, namely D-3 and UP-2. Farm D-3 has no water storage, while farm UP-2 has a small dam and gets water from a seasonal

river. This is consistent with the results from Becu *et al.* (2003), which showed that the position of a farmer's irrigated plots along the canal was a significant factor in how well a farmer would perform economically, with farmers with plots located upstream being more successful compared to farmers with plots located downstream. In the case of the KBV ABM, the position of a farm in the catchment and the type of river it has access to are some factors that influence the level of water stress the farm would get.

The KBV ABM can provide indicators at the farm level, and Figures 5.10, 5.11 and 5.12 show model outputs for farm UP-2. Figure 5.10 shows the water demand, deficit, irrigation and rainfall for farm UP-2 from October 2017 to September 2020. Figure 5.11 shows the farm's water storage volume, and Figure 5.12 shows the average farm water stress.

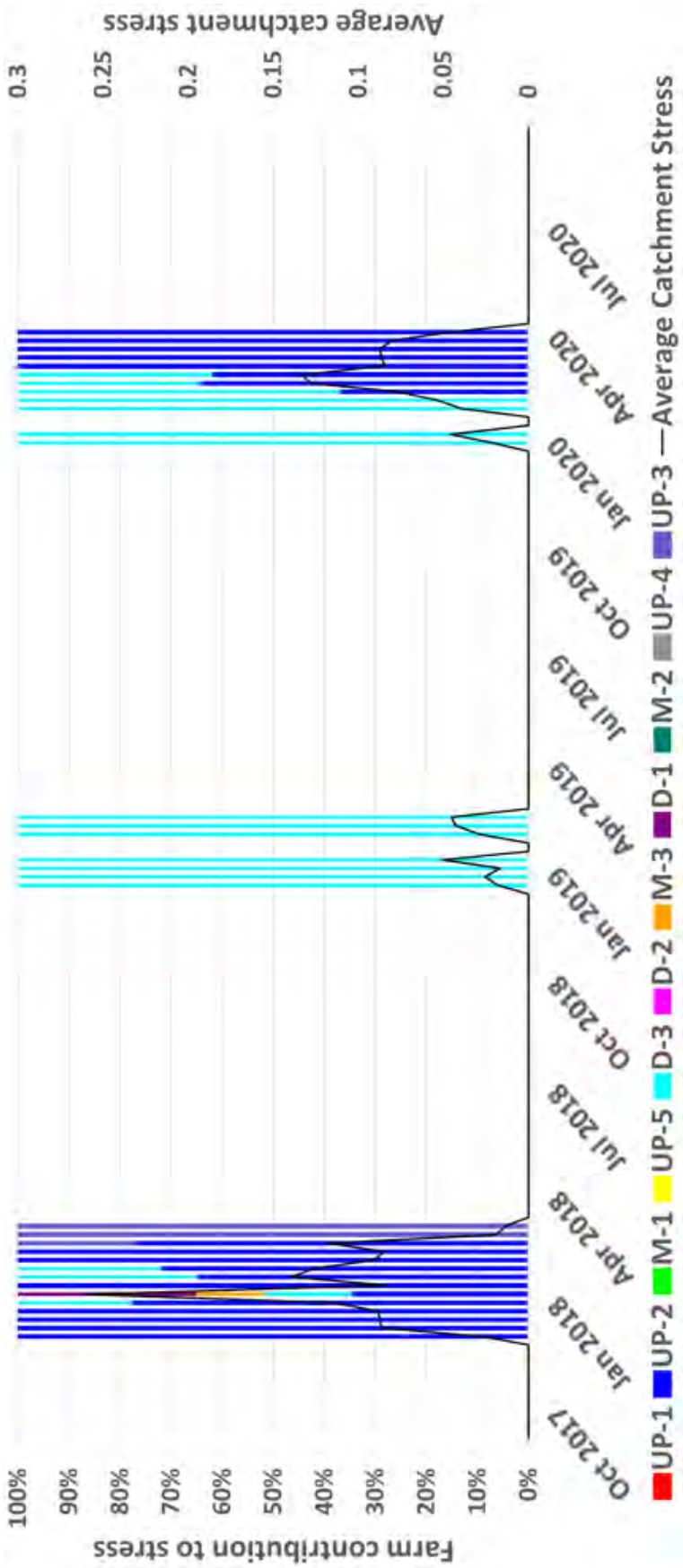

Figure 5.9: Average catchment stress for the period October 2017 to September 2020.

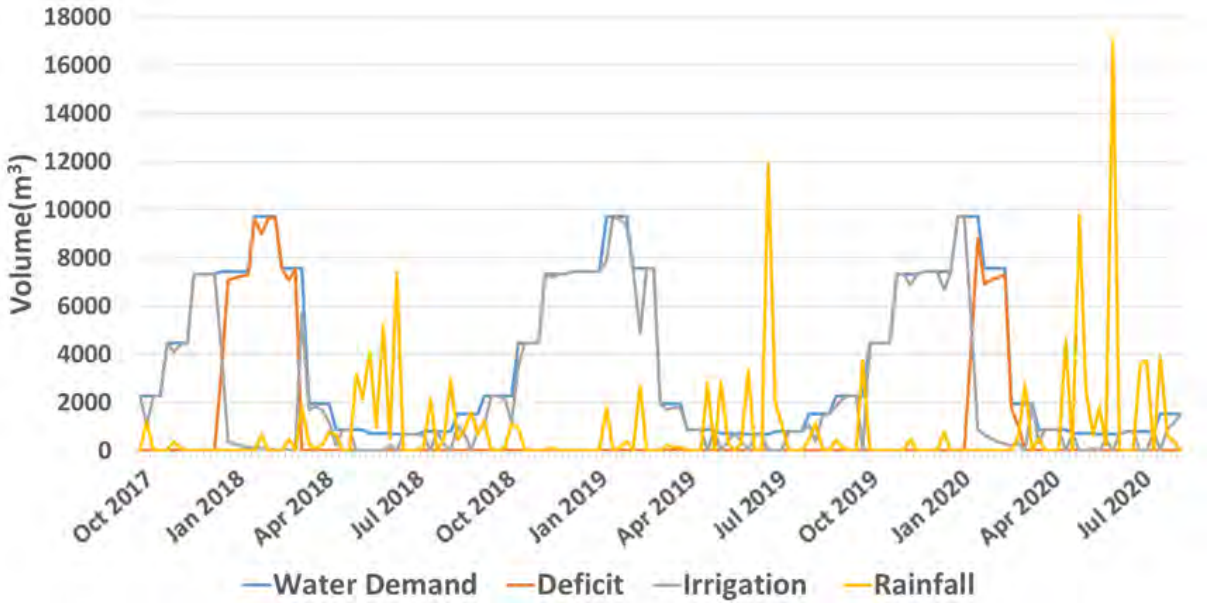

Figure 5.10: Water demand, deficit, irrigation and rainfall for farm UP-2 from October 2017 to September 2020.

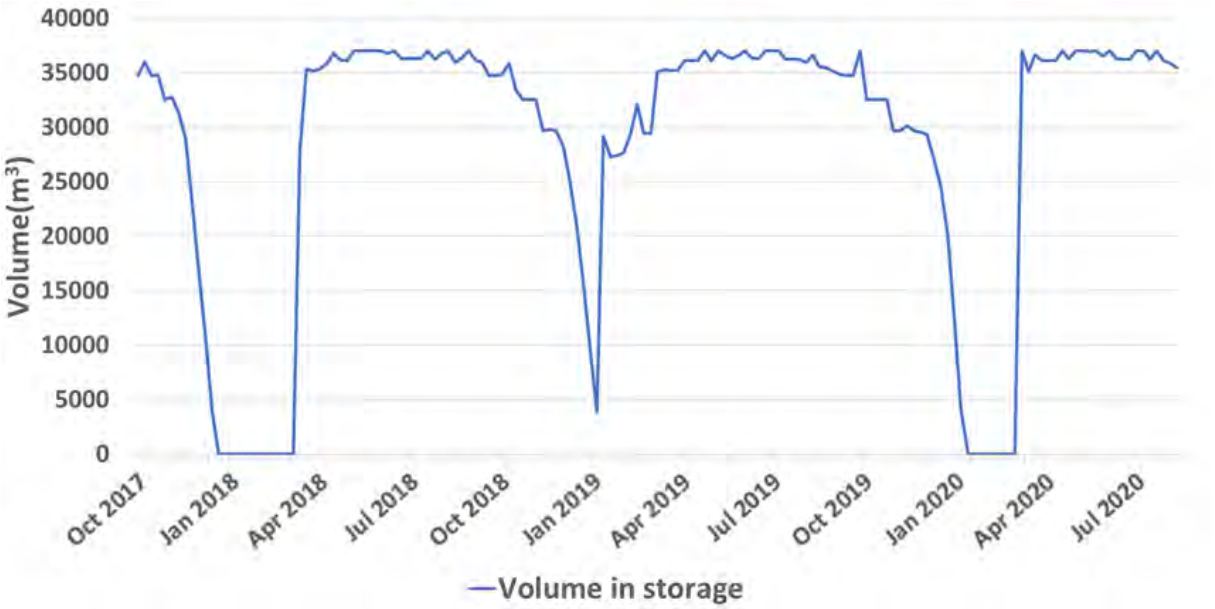

Figure 5.11: Volume of water in storage for farm UP-2 from October 2017 to September 2020.

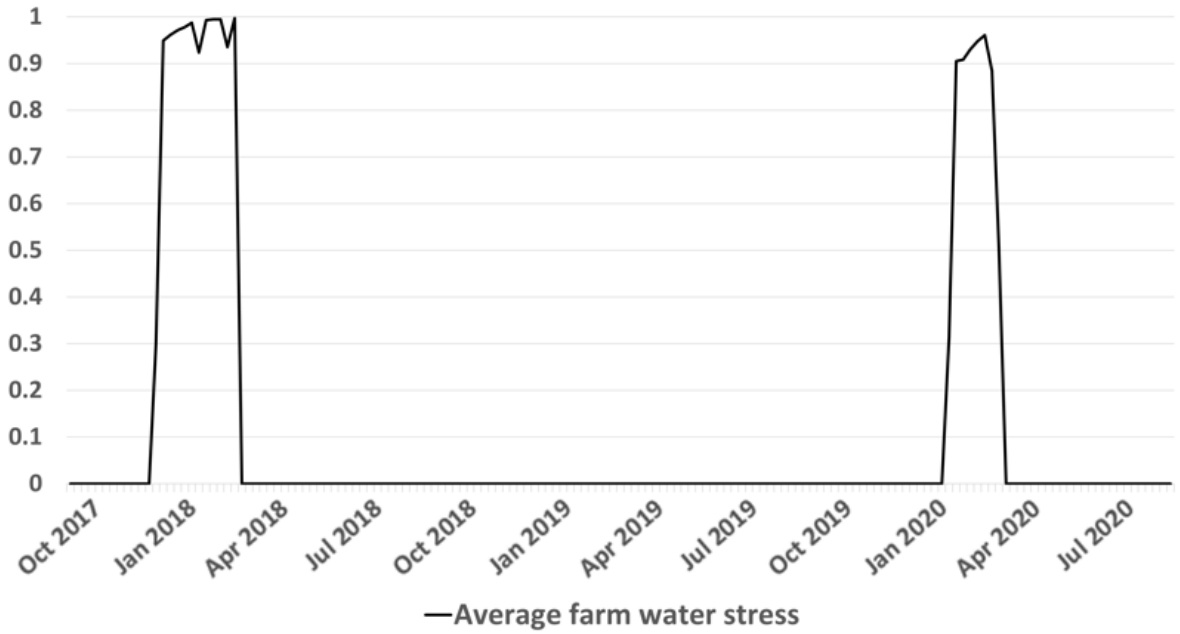

Figure 5.12: Average farm stress for farm UP-2 from October 2017 to September 2020.

The graphs are consistent in that the periods with high water stress coincide with periods with little rainfall and a low volume of water in storage. For example, Figure 5.11 shows that in February 2018, there was no water in storage; Figure 5.10 shows low rainfall, high water demand and a high water deficit for the same period; and Figure 5.12 shows that the water stress was close to one for this period.

These indicators give a comprehensive depiction of the model dynamics. However, the water stress and deficit are for when only surface water is used for irrigation. Section 4.2.2 states that the KBV ABM only considers surface water, but some farms, e.g. farm UP-2, mentioned that they used groundwater during emergencies. Therefore, the actual water shortage might not have been as high as that portrayed in the model.

We shared these results with the catchment coordinator, who stated that the results were realistic, but there was no data to confirm the exact water shortage volumes. The catchment coordinator confirmed that the farms with shortages were realistic but mentioned that farm D-2 also had shortages. The KBV ABM did not show any water shortage for farm D-2. This is because farm D-2 is one of the farms for which we received questionnaire responses, and we used the current land use they provided. The questionnaire stated that they had reduced their cultivation, which explains the model results.

5.12 Chapter summary

This chapter explained the implementation of the conceptual model described in Chapter 3. It described how Cormas' functionality was utilised in implementing the KBV ABM, including the Cormas classes such as `SpatialEntityAggregate` and `ArcEntity` classes. The most important implementation details of the agents were discussed, as well as how indicators could be tracked. Visualisation facilities available in Cormas and how they were used in the KBV ABM were highlighted. It described the verification steps performed, which involved checking if the river network was working as expected and checking the water balance. The chapter mentioned challenges encountered during the implementation of the model and solutions to overcome these and concluded by explaining the validation of the model.

6

Results and Discussion

This chapter discusses the simulated scenarios and their results in detail. As mentioned in Section 4.2.6, six future scenarios were designed to test the usefulness of the KBV ABM. The results from each scenario are presented individually, followed by a discussion and comparison of all the scenarios at the end of the chapter.

6.1 Future climate projections

Future climate projections for the KBV ABM were simulated using the RCA4 model with RCP 4.5 and RCP 8.5 scenarios, bias-corrected using the linear scaling method. The results indicated that, from 2025 to 2030, RCP 4.5 had higher temperatures and lower rainfall than RCP 8.5, while from 2025 to 2060, the opposite trend was observed.

6.2 Calculating the EWR

The EWR for the KBV was calculated using the STREAM tool, with the natural flow rate compared to EWR values representing dry, average, and wet conditions. This approach allowed us to assess whether the EWR was met under different scenarios.

6.3 Scenarios

The stakeholder workshops and survey results showed possible development trajectories in the catchment and some of the stakeholders' concerns. Section 4.1 explains that some farmers intend

to increase the area under cultivation and add new dams in the future. Additionally, some stakeholders wanted to know how climate change would affect the catchment. Scenarios R4, R5 and R6 were suggested by the stakeholders. The scenarios we ran aimed to explore these questions and show how the KBV ABM can be a useful DST. Few previous studies in the KBV reported their results at the farm level; therefore, it was impossible to directly compare the results in this chapter with those in other studies. However, studies whose results show similar trends to those reported in this chapter are mentioned.

As was the case in the validation tests, catchment stress levels are used as metrics for comparison of the scenarios.

6.3.1 Scenario R1: Moderate climate change

One of the objectives of this study was to find out how climate change will affect the KBV region; therefore, this scenario was run to meet this objective. Similar to Gumbo and Kapangaziwiri (2021), we used RCP 4.5 to explore the effects of moderate climate change in the catchment. Validation Test 2 was used as the Baseline scenario.

6.3.1.1 Data used

The scenario used current land use data. The rainfall and streamflow were obtained from the SWAT model, which was run from October 2025 to September 2030, using the RCP 4.5 predicted rainfall and temperature data.

6.3.1.2 Results

Impact on water availability for farms

Figure 6.1 shows the rainfall in the catchment for this period. The graph shows that more rainfall falls in winter than in summer. Figure 6.2 shows the average catchment stress and each farm's contribution to the stress from October 2025 to September 2030. It shows that the highest average catchment stress was 0.4, which occurred in the summer of 2028. This is a 38% increase

compared to the peak catchment water stress for the years 2017 to 2020 shown in the Baseline scenario, which was 0.25.

Surprisingly, there was only a slight increase in the number of farms with water shortages, with the Baseline scenario showing six farms and this scenario showing seven farms with water shortages. The new farm with water shortage was farm D-2. However, this scenario showed that in more summers, multiple farms had water shortages (summer periods in the hydrological years 2027/28 and 2029/30) compared to the Baseline, where the summer of 2017/18 had five farms with shortages, and that of 2019/20 had two farms affected.

Impact on EWR

Figure 6.3 shows the river flow rate and the EWR at the catchment outlet from October 2025 to September 2030. The graph shows that the river flow rate generally followed the rainfall pattern, with most water flowing in winter and less in summer. Similarly, the EWR was higher in winter compared to summer. The figure shows that in summer, the river flow was almost equal to the EWR, and in some cases, the river flow was less than the EWR.

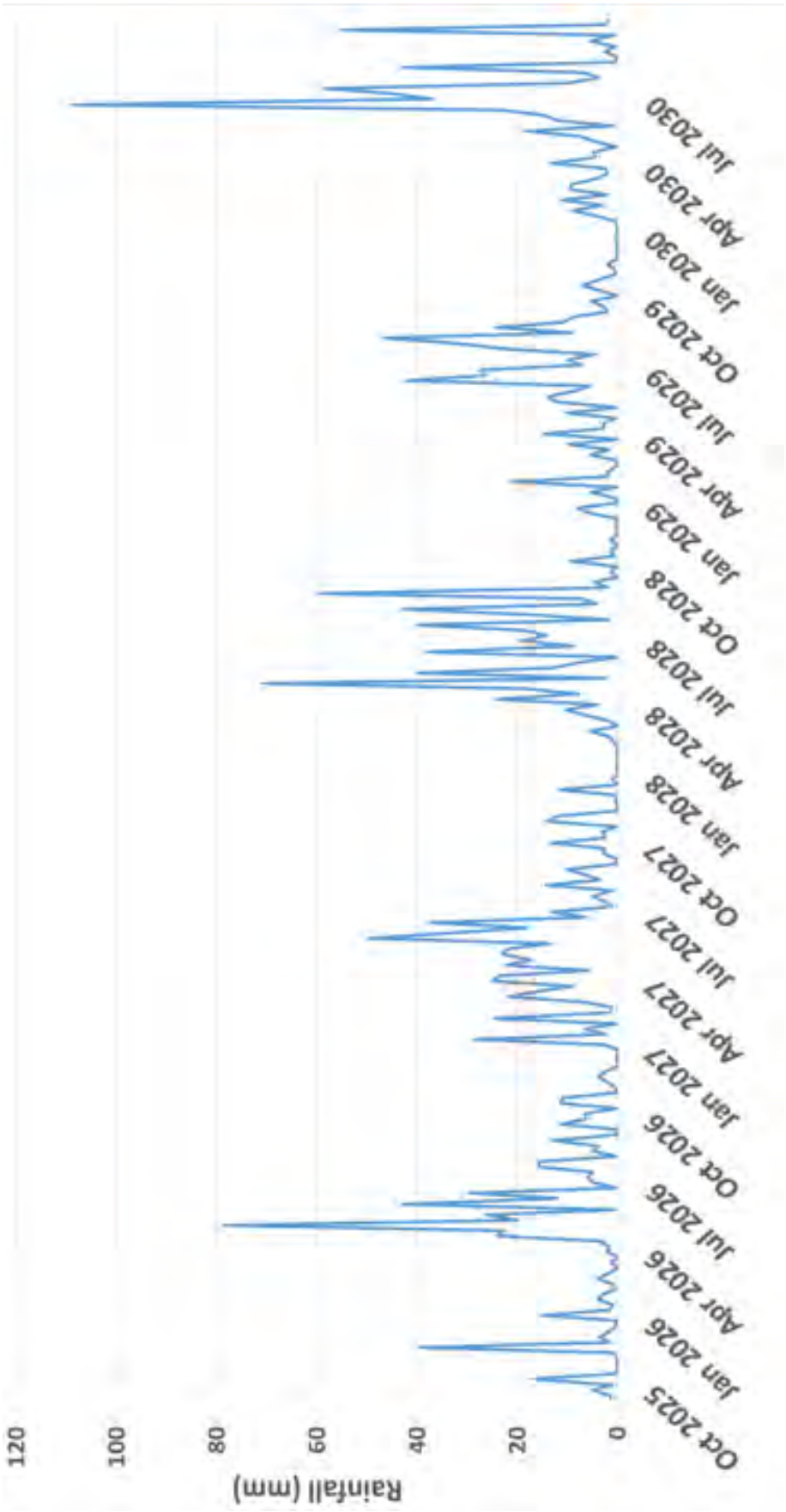

Figure 6.1: Scenario R1: Catchment rainfall from October 2025 to September 2030.

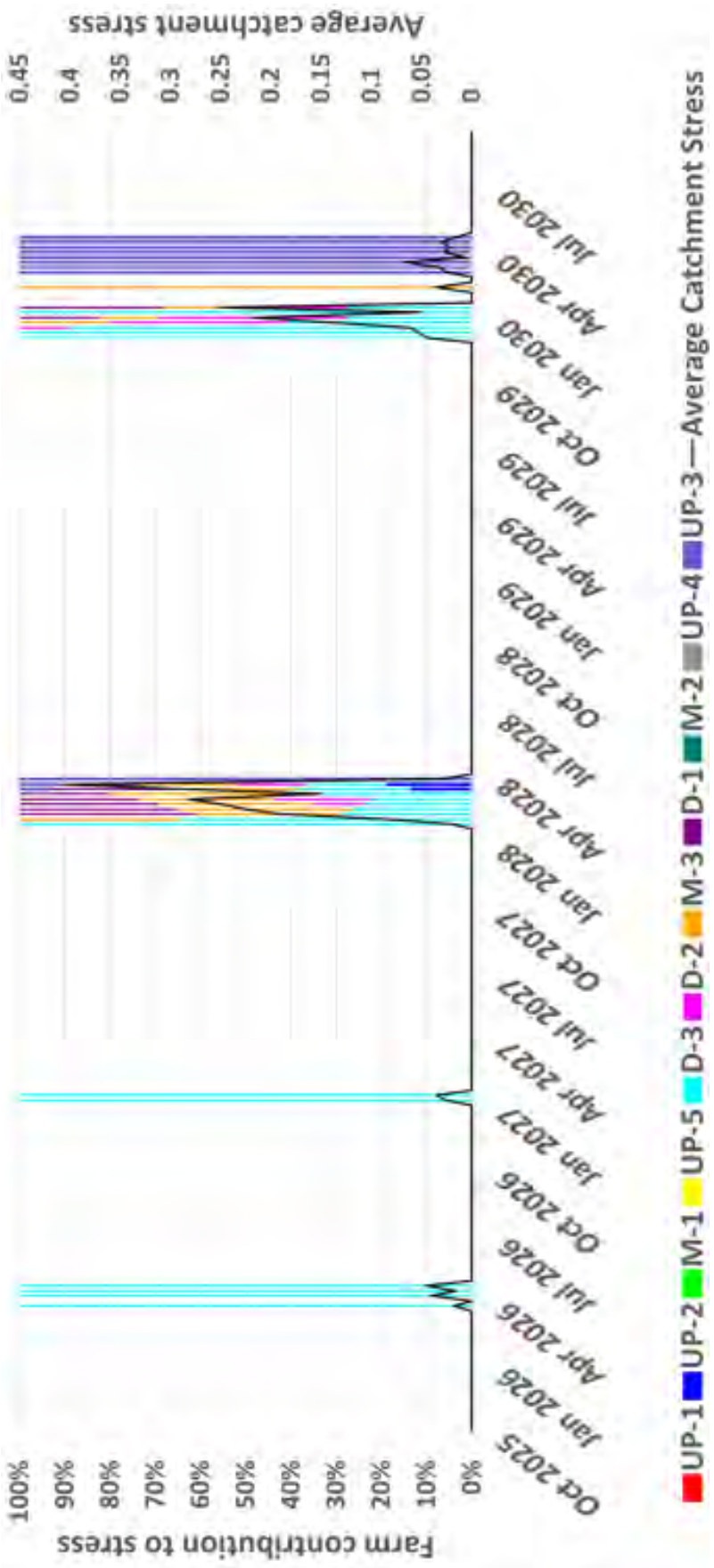

Figure 6.2: Scenario R1: Average catchment stress and each farm's contribution to stress from October 2025 to September 2030.

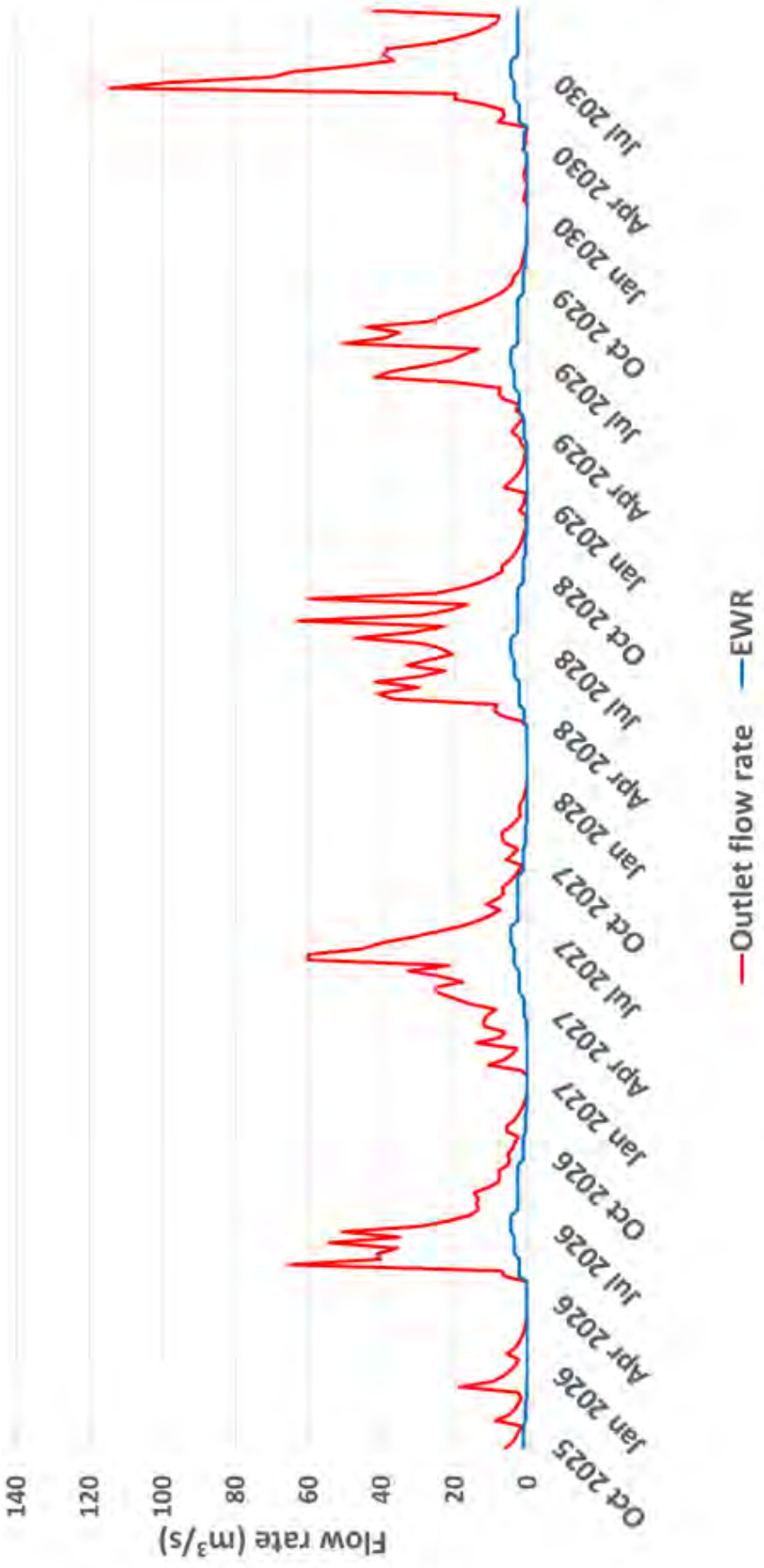

Figure 6.3: Scenario R1: Outlet flow and EWR October 2025 to September 2030.

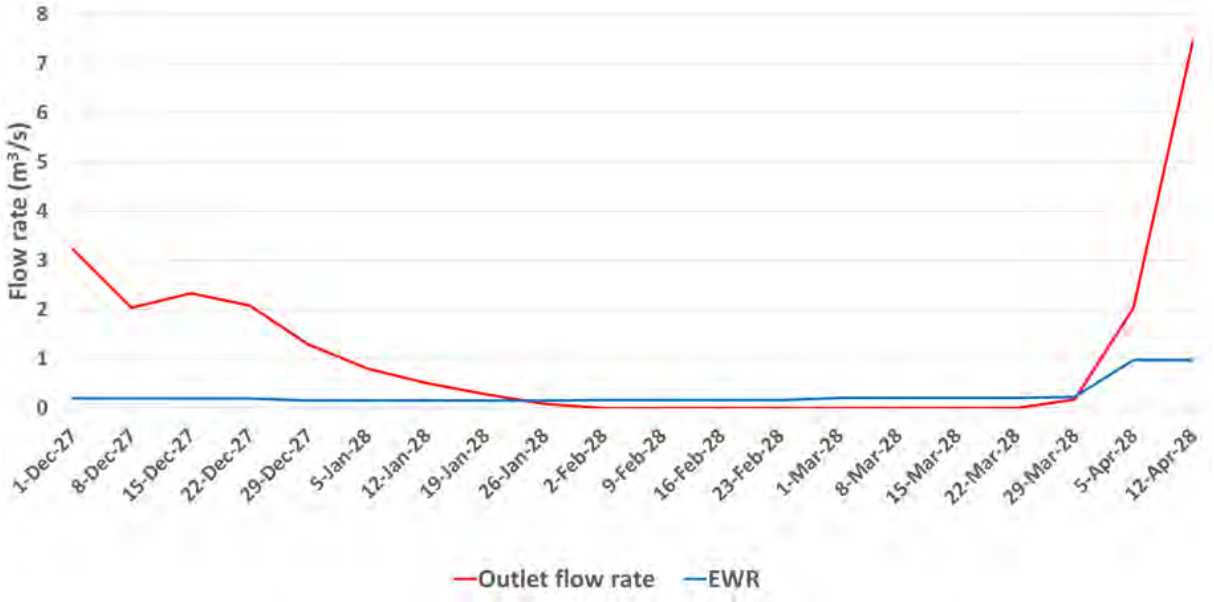

Figure 6.4: Scenario R1: Outlet flow and EWR December 2027 to April 2028.

Table 6.1: Scenario R1: Number of weeks EWR was not met in each hydrological year from October 2025 to September 2030.

Hydrological Year	2025/26	2026/27	2027/28	2028/29	2029/2030
Number of weeks EWR was not met	5	3	10	1	14

Figure 6.4 shows the river flow rate and the EWR at the catchment outlet from December 2027 to April 2028. At the start of December, the river flow rate exceeded the EWR until the end of January. From this point until the end of March, the river flow rate was lower than the EWR. This was because of the low rainfall that fell during this period, as illustrated in Figure 6.1, which shows low rainfall for January 2028. For the Baseline scenario, Figure 5.10 also confirms that January is one of the months with high water demand, which means farms pumped high volumes of water from the river for irrigation, contributing to the low river flow.

Table 6.1 shows that for 33 weeks, EWR was not met for the period October 2025 to September 2030, with 2027/28 and 2029/30 hydrological years being the worst affected. The least affected year was 2028/29, with only 1 week where EWR was not met.

Given that RCP 4.5 predictions are worse in terms of rainfall for the intermediate future (i.e. 2025-2030) than the RCP 8.5 predictions (presented in Section 6.3.2), we reran this scenario to predict water availability in the catchment in the far future under moderate climate change.

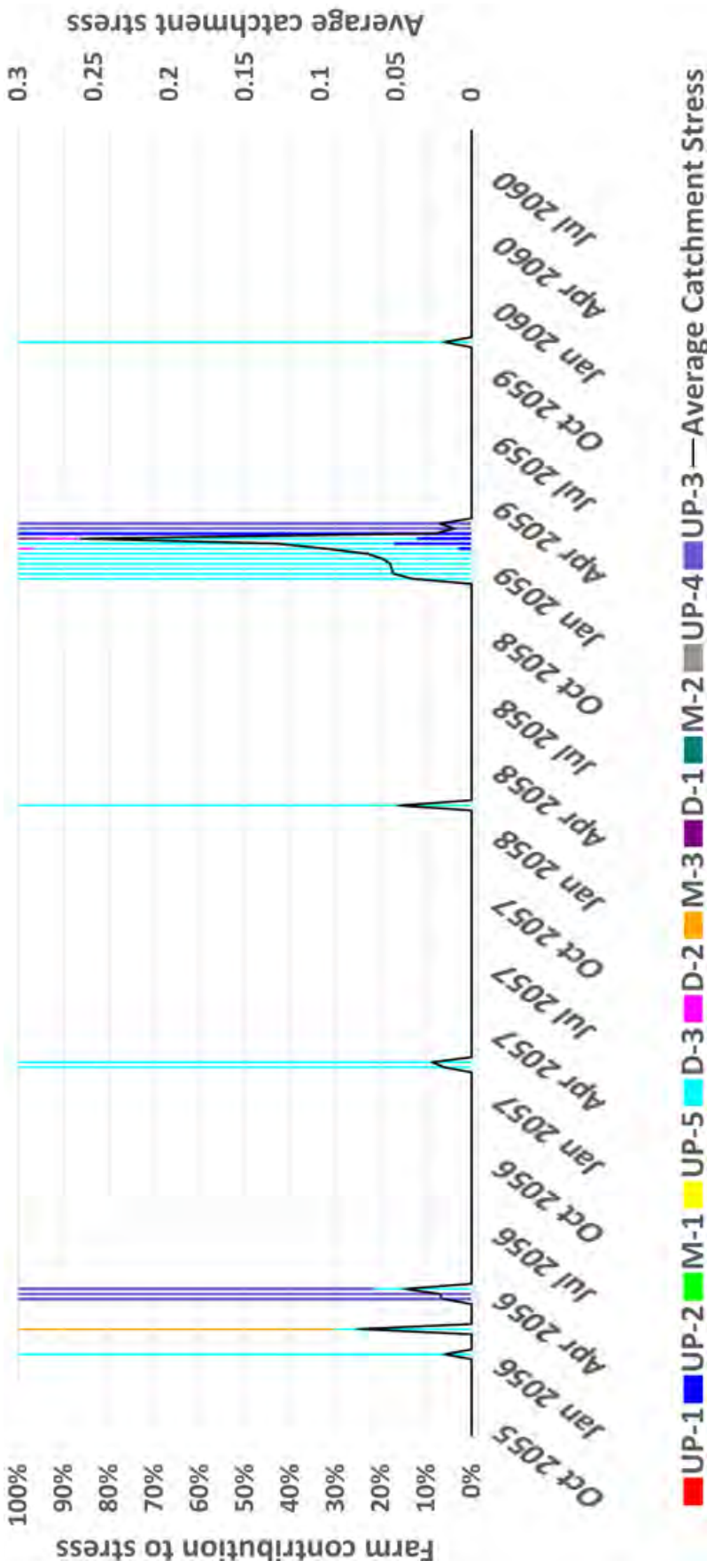

Figure 6.5: Scenario R1: Average catchment stress and each farm's contribution to stress from October 2055 to September 2060 under moderate climate change.

Rainfall and streamflow were obtained from the SWAT model from October 2055 to September 2060, using RCP 4.5 predicted rainfall and temperature. Figure 6.5 shows the average catchment stress and each farm's contribution to the stress under moderate climate change from October 2055 to September 2060. This figure also shows maximum average catchment stress of 0.25, with six farms suffering from water stress.

6.3.2 Scenario R2: Extreme climate change

This scenario was run to explore the impacts of extreme climate change on the catchment, and as before, Validation Test 2 was used as the Baseline scenario.

6.3.2.1 Data used

The scenario used current land use data. The rainfall and streamflow values were obtained from the SWAT model, which was run from October 2025 to September 2030, using RCP 8.5 predicted rainfall and temperature.

6.3.2.2 Results

Figure 6.6 shows rainfall in the catchment for this period. The graph shows higher rainfall under the extreme climate change scenario for this period compared to the moderate climate change.

Figure 6.7 shows the average catchment water stress and each farm's contribution to the stress from October 2025 to September 2030. The water availability for this scenario was higher than that experienced in the moderate climate change scenario. This is because, for the 2025 to 2030 period, the RCP 4.5 data has a higher average temperature and lower average rainfall than the RCP 8.5 data.

The scenario showed that the maximum average stress was 0.25, almost the same as the maximum average water stress in the Baseline scenario, which was 0.26. However, this scenario had three farms with water shortages and fewer weeks with water shortages compared to the Baseline scenario, which had five farms with water shortages and more weeks with water shortages.

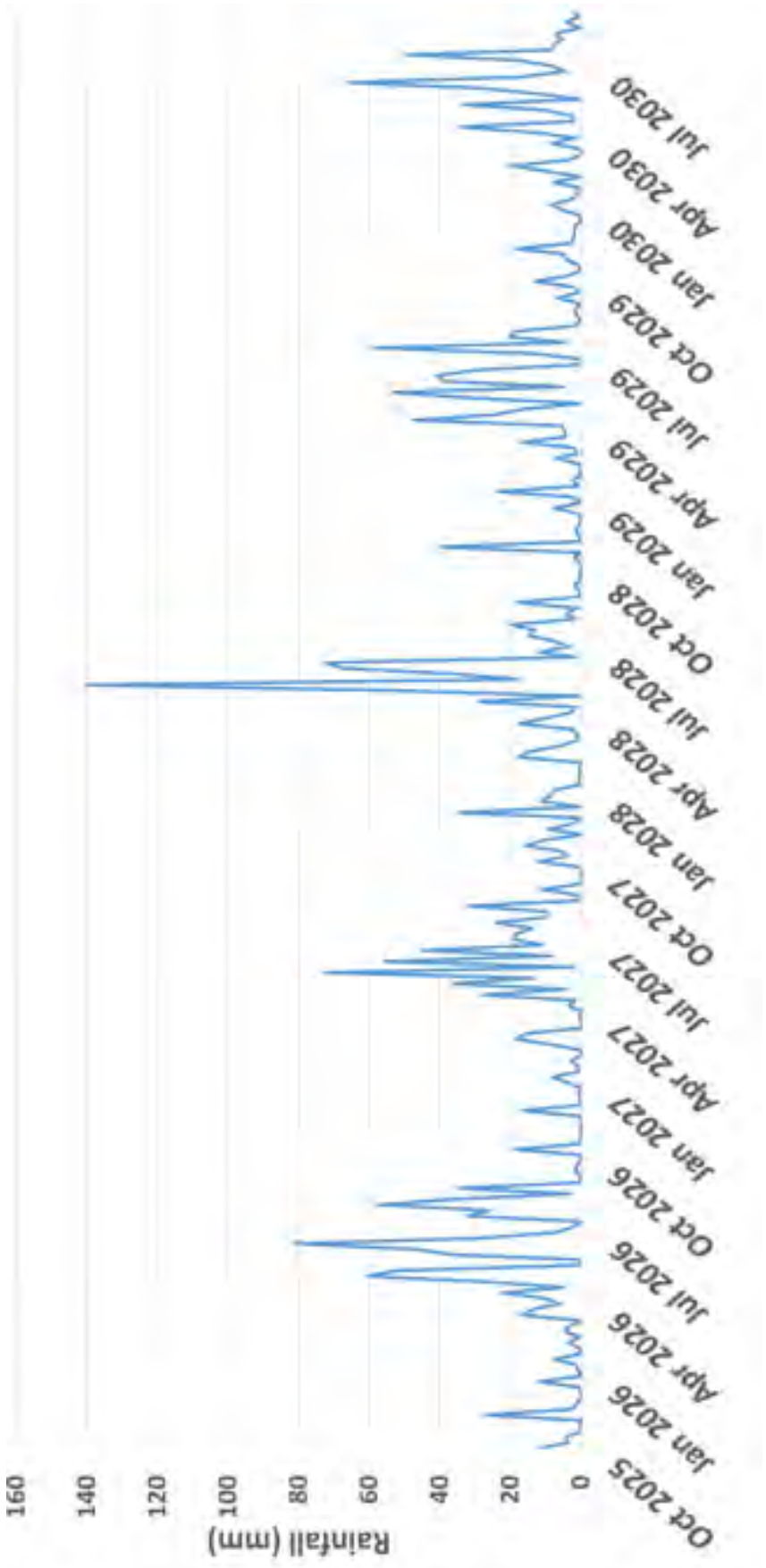

Figure 6.6: Scenario R2: Catchment rainfall from October 2025 to September 2030.

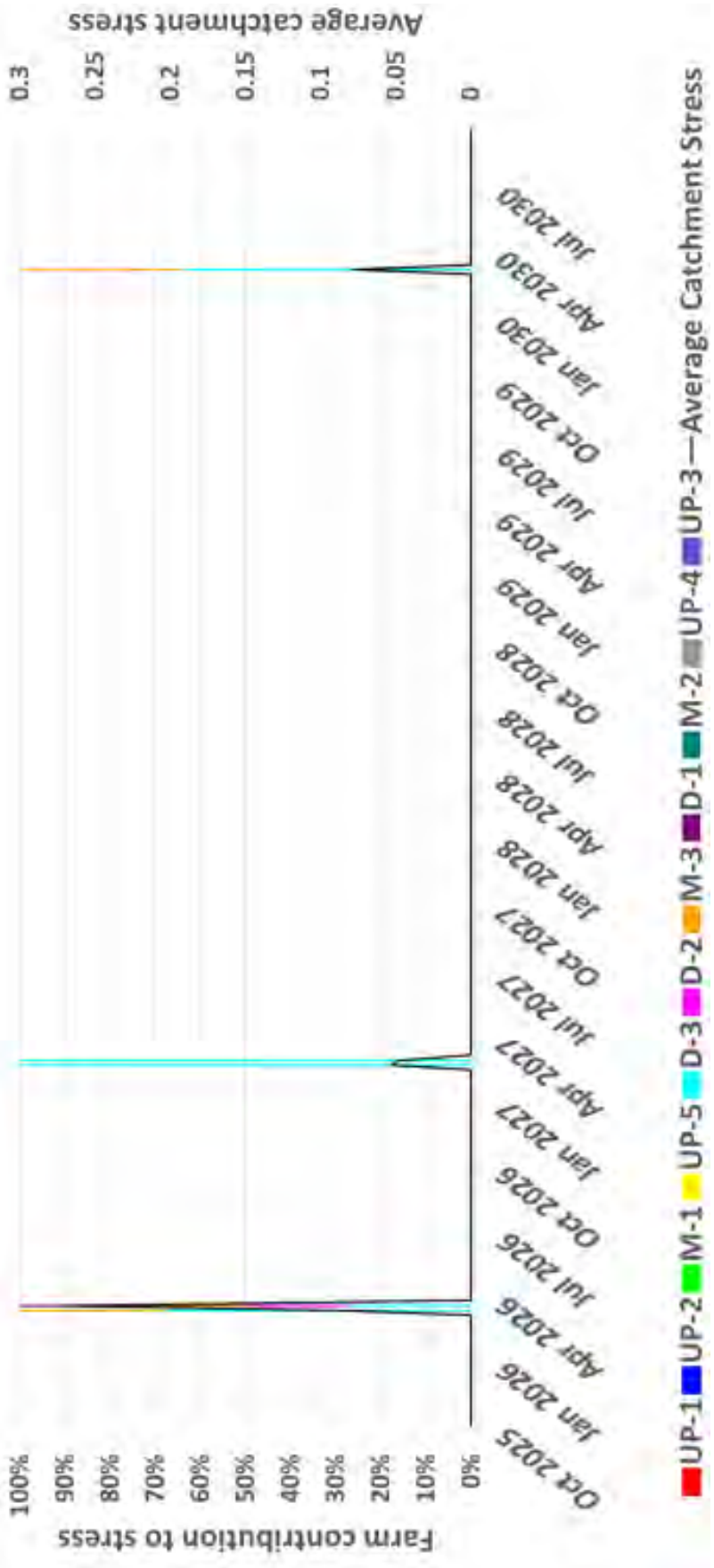

Figure 6.7: Scenario R2: Average catchment stress and each farm's contribution to stress from October 2025 to September 2030.

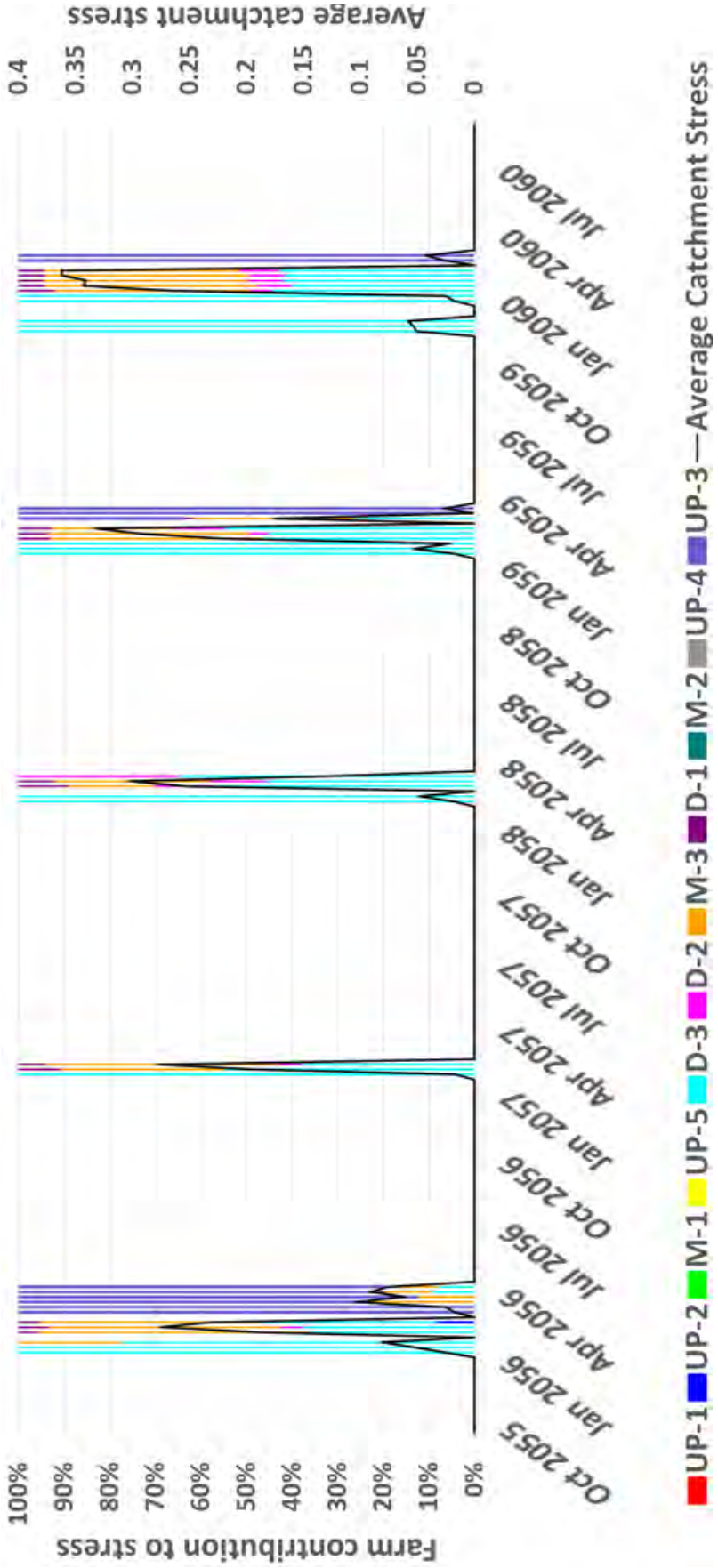

Figure 6.8: Scenario R2: Average catchment stress and each farm's contribution to stress from October 2055 to September 2060 under extreme climate change.

Similar to what was done for Scenario R1, we reran this scenario from 2055 to 2060. Figure 6.8 shows the average catchment stress and each farm's contribution to the stress under extreme climate change from October 2055 to September 2060. It shows a maximum catchment stress of 0.35 with seven farms having water shortages, while Figure 6.5 shows a maximum average catchment stress of 0.25, with six farms suffering from water stress. This shows that the extreme climate change scenario R2 has lower water availability for this period than the moderate climate change scenario, similar to the trends reported by Gumbo and Kapangaziwiri (2021) and Tanner *et al.* (2022).

6.3.3 Scenario R3: Increase in hectarage of main crops by upstream farms under moderate climate change

The survey responses showed that some farmers planned to expand land under cultivation. This scenario was designed to explore the impacts that cultivation expansion might have in the catchment. Scenario R1 was used as the Baseline scenario.

6.3.3.1 Data used

We increased the hectarage of upstream farms' main crops by 20%. The rainfall and streamflow were obtained from the SWAT model, which was run from October 2025 to September 2030, using RCP 4.5 predicted rainfall data.

6.3.3.2 Results

Figure 6.9 shows the average catchment and each farm's contribution to the stress from October 2025 to September 2030. The diagram shows a slight worsening of water availability for this scenario compared with the Baseline scenario. The maximum average water stress for this scenario was 0.45, an increase of 12.5 % compared to the maximum average water stress shown in the Baseline scenario.

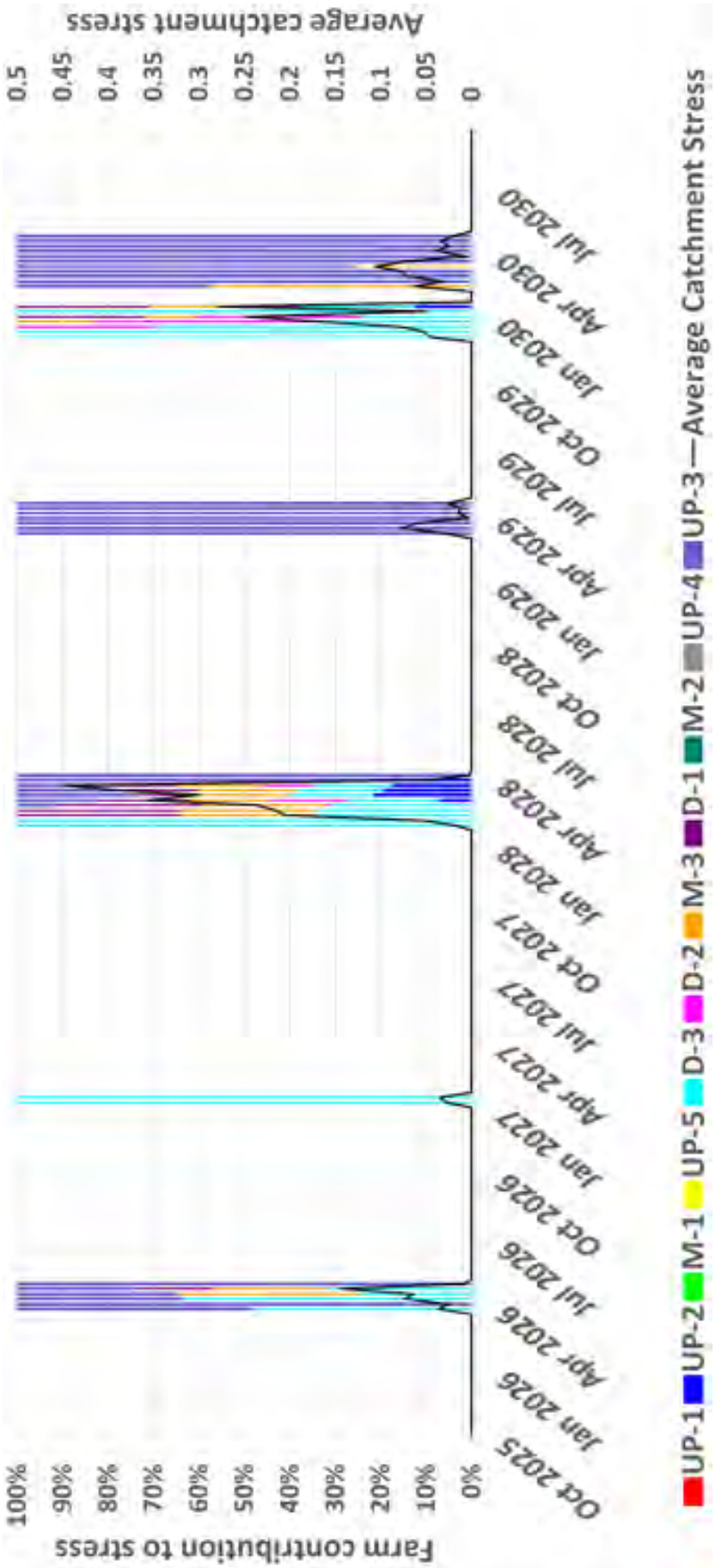

Figure 6.9: Scenario R3: Average catchment stress and each farm's contribution to stress from October 2025 to September 2030.

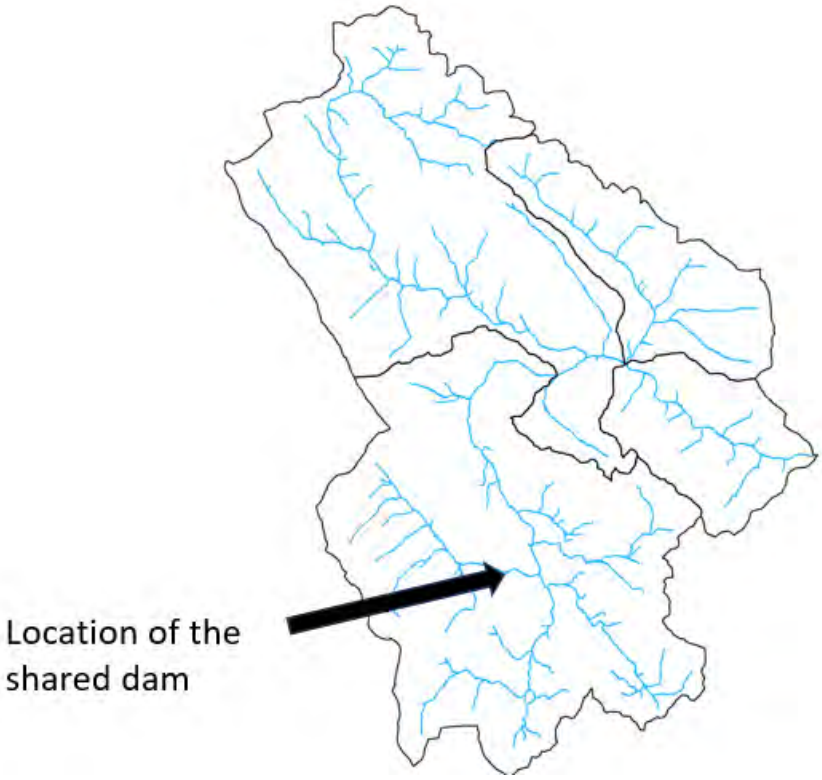

Figure 6.10: Location of the shared dam.

Because we used one-way coupling between the SWAT and KBV ABM, this scenario has the weakness of not representing the effects of Land Use Land Cover (LULC) changes on groundwater recharge, which in turn reduces infiltration (Gyamfi *et al.*, 2017) and can affect the baseflow component of the river flow. As explained in Section 2.2, groundwater contributes to a river's flow. This means the water stress result in this scenario could be higher due to reduced groundwater recharge.

6.3.4 Scenario R4: Shared dam and 10% increase in dam capacities under moderate climate change

The survey showed that some farmers were planning to construct new dams. Howard (2010) explored the viability of building a new dam on the Hex River; therefore, we explored a scenario where farms increase their storage capacities, and a shared dam is added on the Hex River. Figure 6.10 shows the dam's location.

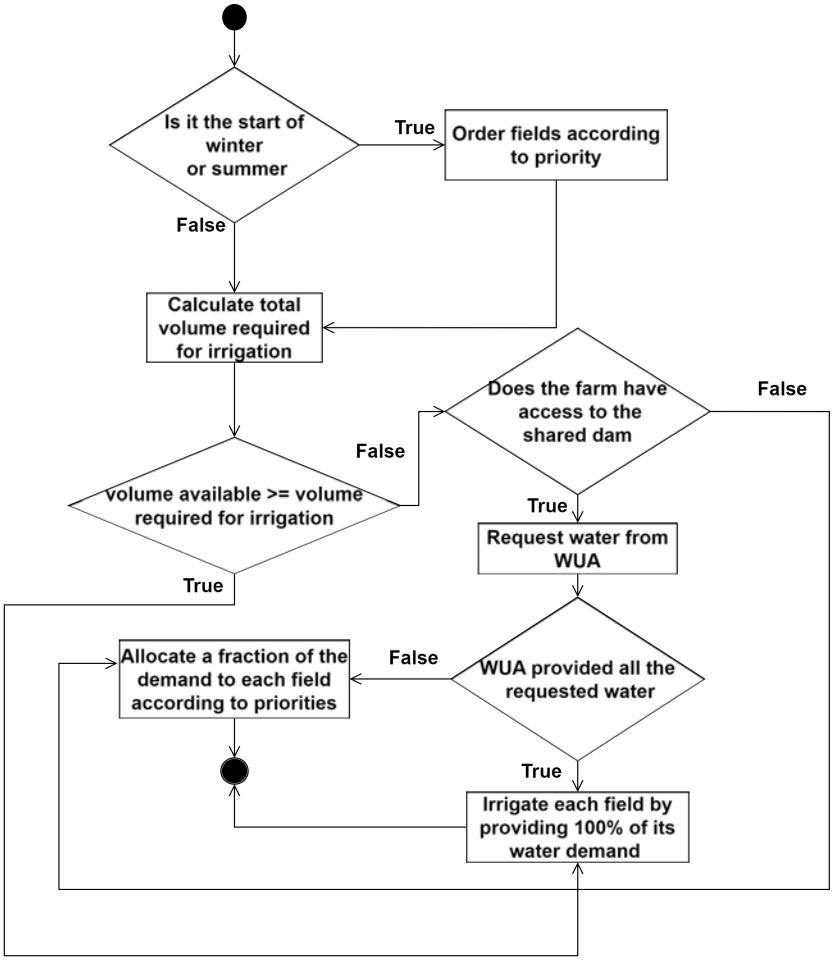

Figure 6.11: Modification to the irrigation process of `Farms`.

6.3.4.1 Modification of the model

As explained in Section 4.2.3.5, the WUA is the shared dam controller, and those farms with access to the shared dam make water requests to the WUA. Various modifications were made to the model to explore this scenario.

Changes to irrigation strategy

Figure 6.11 shows the modification to the irrigation behaviour of the Farm agents described in Section 4.2.5.1. The difference in the irrigation process occurs when a Farm agent does not have enough water for irrigation. The flowchart shows that in this case, a Farm checks if it has access to the shared dam. Only farms D-1, D-2, D-3 and M-3 can access the shared dam in this scenario. If a Farm has access to the shared dam, it requests water from the WUA agent. The Farm agent

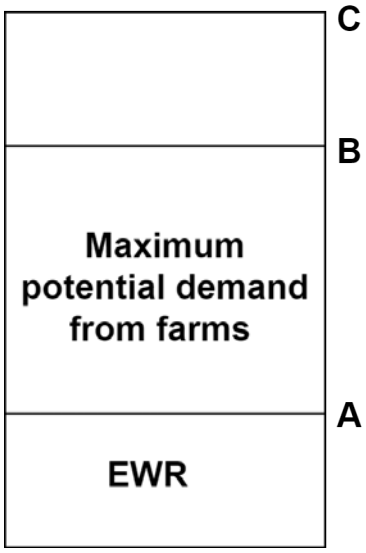

Figure 6.12: Shared dam volume thresholds.

checks if the WUA agent has provided all the requested water. The Farm agent then irrigates each of its fields with 100% of their irrigation water demand if all the water has been provided. However, if not all the water is provided, the Farm agent uses crop priorities to determine the irrigation water demand volume to provide to each field.

Modification of the WUA agent's behavior

The WUA is responsible for responding to water requests from Farm agents and releasing water into the river for EWR.

Figure 6.12 shows the thresholds used in controlling how the WUA responds to Farm water requests. A represents the fraction of the dam capacity (C) reserved for EWR. If the dam volume is below this threshold, the WUA cannot provide any water to Farms. The threshold was set to 30% of the shared dam capacity. Because the model executes RiverSegments in order from upstream to downstream, the WUA cannot simultaneously receive demands from all the Farms. Therefore, we introduced threshold B, the total maximum water demand of the Farms with access to the shared dam. The WUA shares the water equally amongst the Farms. The volume of water available for sharing between farms is the difference between the shared dam's volume and A. If the shared dam's volume is below B, each Farm agent will get a maximum volume given by the equation:

$$\frac{1}{number\ of\ farms\ accessing\ shared\ dam} \times (shared\ dam\ volume - A) \tag{6.1}$$

However, if the shared dam's volume exceeds B, each Farm will receive all its requested water. The water is transferred directly to the Farm that requested the water. This decision was made because if the water is supplied via the river, it will reach the requesting Farm only in the following timestep, and there is a possibility of other Farms pumping the water.

The WUA releases water for EWR each week. The volume of water released was set to 5% of the shared dam capacity. However, the WUA doubles the volume it releases for EWR if the EWR was not met in the previous timestep.

6.3.4.2 Data used

We increased the storage of all farms that do not have access to the shared dam by 10%. A shared dam with 1 094 627 m^3 capacity, which is 10% of the total initial dam capacities, was added at the Hex River. The rainfall and streamflow were obtained from the SWAT model, which was run from October 2025 to September 2030, using RCP 4.5 predicted rainfall data.

6.3.4.3 Results

Figure 6.13 shows the average catchment stress and each farm's contribution to the stress from October 2025 to September 2030. The maximum average water stress experienced in the catchment was 0.14, which is 65% lower than that of the Baseline scenario R1. Three farms experienced water shortages, an improvement compared to the Baseline scenario, with only six farms experiencing water shortages.

Although farm D-3 was one of the farms with access to the shared dam, it experienced some weeks of water shortages. Figure 6.13 shows that the farm had water shortages between January and April 2028 and in January 2020. These shortages were caused by low volumes in the shared dam, which meant that the WUA agent could not provide water to any Farm agents as the shared dam's volume was below the threshold A.

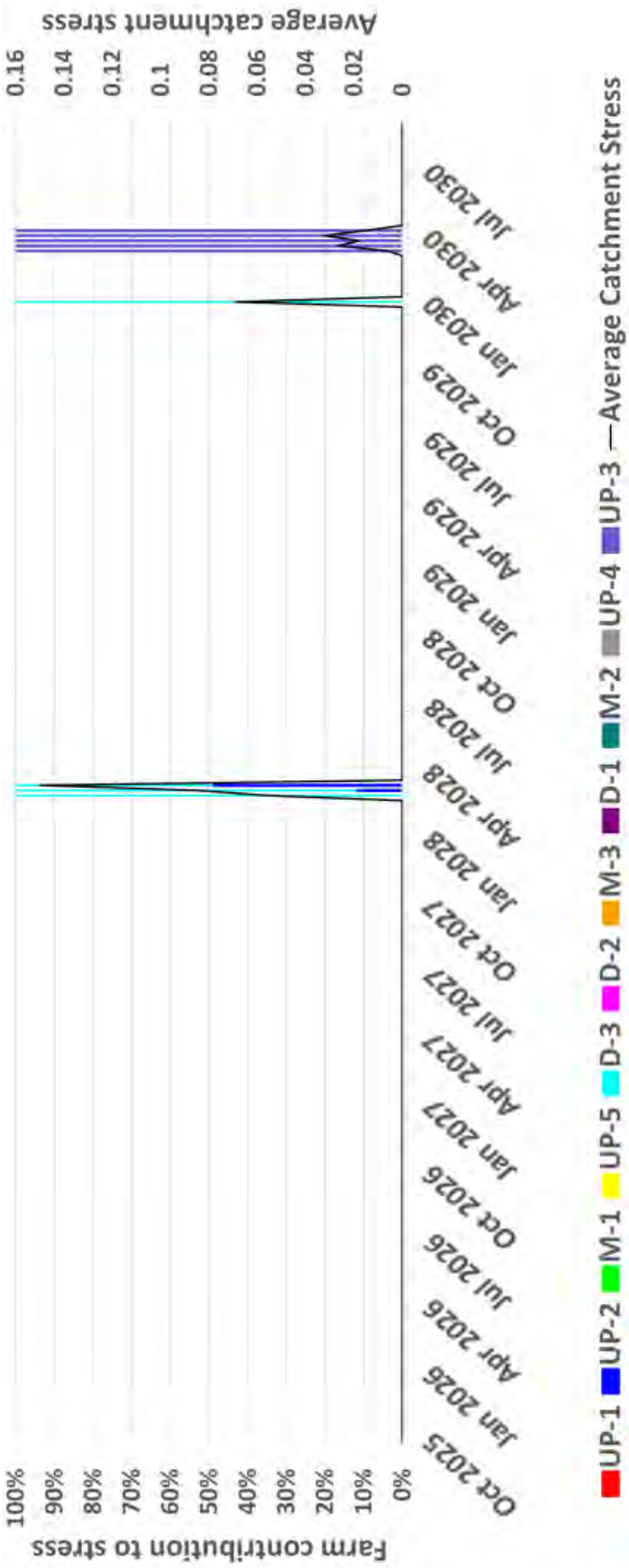

Figure 6.13: Scenario R4: Average catchment stress and each farm's contribution to stress from October 2025 to September 2030.

Farms UP-2 and UP-3 still had water shortages, but these were less compared to the water shortages they had in the Baseline scenario R1. This indicates that the 10% increase in dam capacity for farms without access to the shared dam helped improve water availability for these farms, but this was insufficient to ensure water availability for the whole period.

6.3.5 Scenario R5: Shared dam and 20% increase in dam capacities under moderate climate change

After we presented the model results of Scenario R4 at the third workshop, some stakeholders asked us to repeat the scenario but using a 20% increase in dam capacities. We ran a scenario similar to Scenario R4 but using a 20% increase in existing dam capacities and increased the shared dam's capacity by 20% as well. Scenario R1 was the Baseline scenario.

6.3.5.1 Data used

We increased the storages of all farms that did not have access to the shared dam by 20%. The capacity of the shared dam at the Hex River was increased to 2 189 254 m^3, which is 20% of the total initial dam capacities. The rainfall and streamflow were obtained from the SWAT model, which was run from October 2025 to September 2030, using RCP 4.5 predicted rainfall and temperature.

The Farm and the WUA agents' behaviour agent was the same as that described for Scenario R4.

6.3.5.2 Results

Figure 6.14 shows the average catchment stress and each farm's contribution to the stress from October 2025 to September 2030. There was a high increase in water availability for farms. Only one farm had a water shortage, and the peak average water stress in the catchment was 0.27. This scenario performed better than both the Baseline scenario R1 and Scenario R4. The scenario performed better than Scenario R4 because of the increased dam capacities, which meant most farms had enough water for irrigation. The new shared dam capacity ensured that those farms that relied on the dam for irrigation water were always fully supplied.

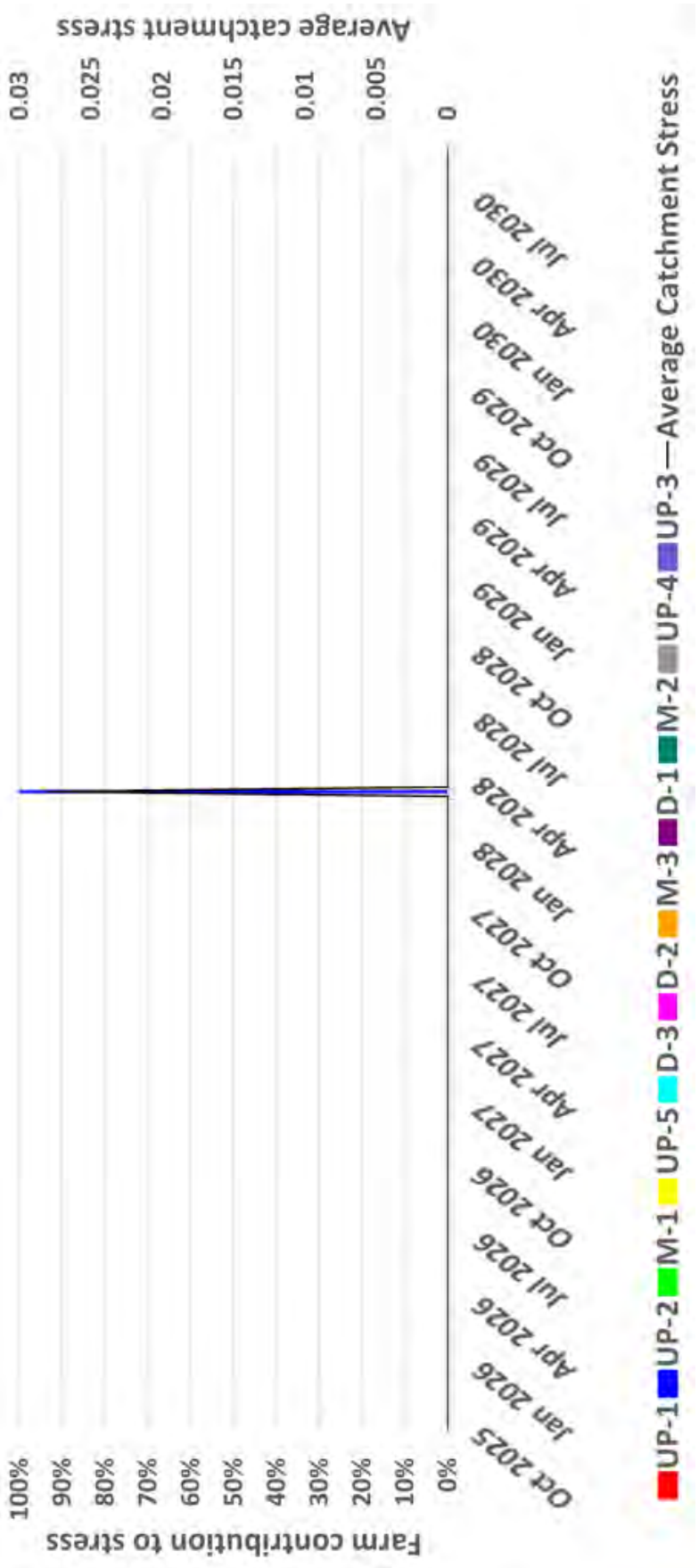

Figure 6.14: Scenario R5: Catchment stress from October 2025 to September 2030.

6.3.6 Scenario R6: Water releases by two big dams in the catchment

The catchment manager stated that two farms owning some of the biggest dams in the catchment had, in the past, released a steady pulse from their dams during summer to maintain river flow. Releases were not made when the dams reached about 20-30% capacity to secure water availability for the farmers in case winter rains were late. However, these releases are no longer being made. One of the reasons for this was that the farms had expanded, meaning they required more water for irrigation (Theron, 2023). Scenario R1 was used as the Baseline scenario for comparison purposes.

6.3.7 Modifications required to the ABM

Modifications to support this scenario were made to the Farm agents' behaviour. A `releasesWater` attribute was added to the `Farm` class, which was set to `true` for Farm agents that own the dams that can release water for environment flows. When a Farm finishes irrigating, it decides whether to release water and the decision is based on three factors. The Farm agent's `releasesWater` attribute must be `true`, it should be summer, and the agent's Dam volume must be greater than 30% of the Dam's capacity. If these conditions are satisfied, the Farm releases water whose volume is 2% of the dam's capacity. The reason we used 2% was that if the percentage was less than 2%, there was no improvement in river flow, and if the percentage was greater than 2%, there was an increase in average catchment stress with the Farms releasing the water most seriously affected.

6.3.8 Data used

The scenario used current land use data. The rainfall and streamflow were obtained from the SWAT model, which was run from October 2025 to September 2030, using RCP 4.5 predicted rainfall and temperature data.

6.3.9 Results

The results show that maximum catchment water stress increased from 4 to 4.5. The increase was due to those farms that made the releases having higher water shortages than in the Baseline

Table 6.2: Scenario R6: Number of weeks EWR was not met in each hydrological year from October 2025 to September 2030.

Hydrological Year	2025/26	2026/27	2027/28	2028/29	2029/2030
Number of weeks EWR was not met	7	1	10	1	10

scenario R1. However, there was an improvement in river flow as expected.

Table 6.2 shows that the EWR was not met for 29 weeks from October 2025 to September 2030, which is a slight improvement compared to the 33 weeks where EWR was not met in the Baseline scenario R1. Although there was a general improvement in river flow, for the 2025/26 hydrological year, the Baseline scenario R1 had fewer weeks when EWR was not met, which was five compared to this scenario's seven weeks. The increase in the number of weeks where EWR was not met was due to the higher volume of water extracted by the farms making water releases in this scenario compared to the volume they extracted in the Baseline scenario R1. However, this did not occur in the other years, and the water releases positively impacted river flow. A similar pattern was observed by Khan *et al.* (2017), who noted that there were instances where water releases by an agent would result in lower river flow compared to when an agent did not release water.

This scenario highlights the challenges of augmenting dry season river flow using present-day dam capacities. As already stated, such a scheme existed in the past. However, these releases are no longer being made due to increased water demand, particularly by those farms that could make water releases. The peak catchment average water stress increase (with those farms making water releases contributing more to the stress) shows that although there was an improvement in river flow, the releases are not sustainable due to their negative impact on the farms making the releases.

6.4 Discussion of scenario results

This section compares RCP 4.5 and 8.5 using their water effect on water availability in the near and far future. Scenarios R1, R3, R4, R5, and R6 are compared using their impact on water availability. Scenarios R1, R4, R5 and R6 are then compared using their effect on environmental flows. In both comparisons, Scenario R1 is used as the Baseline scenario.

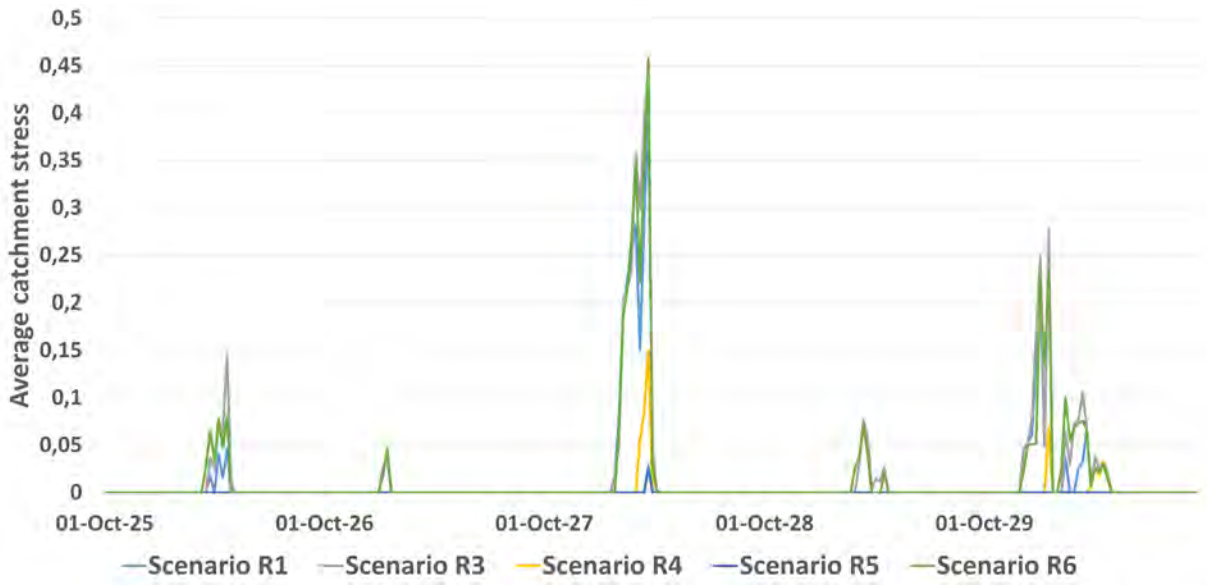

Figure 6.15: Comparison of water availability for farms under the future scenarios.

6.4.1 Comparison of RCP 4.5 and 8.5

The water availability under RCP 4.5 and 8.5 differs depending on the period used. Section 6.3.1 showed that under RCP 4.5, water availability was lower from October 2025 to September 2030 compared to October 2055 to September 2060. In contrast, Section 6.3.2 showed that under RCP 8.5, water availability was higher from October 2025 to September 2030 compared to October 2055 to September 2060. RCP 4.5 had lower water availability than RCP 8.5 from October 2025 to September 2030; however, RCP 4.5 had higher water availability than RCP 8.5 from October 2055 to September 2060.

As explained in Section 2.4, the IPCC defines RCP 4.5 as a carbon emission scenario where carbon emissions peak in 2040, while RCP 8.5 is a scenario where carbon emissions peak in 2100 (Pachauri *et al.*, 2014). This means the effects of climate change are more noticeable in later years compared to earlier years.

6.4.2 Comparison of water availability under the different future scenarios

Figure 6.15 shows the average catchment water stress under all the future scenarios except Scenario R2 because this uses RCP 8.5 data. As expected, Scenario R5 had the lowest water stress for the whole period due to the 20% increase in dam capacities and the addition of the shared dam.

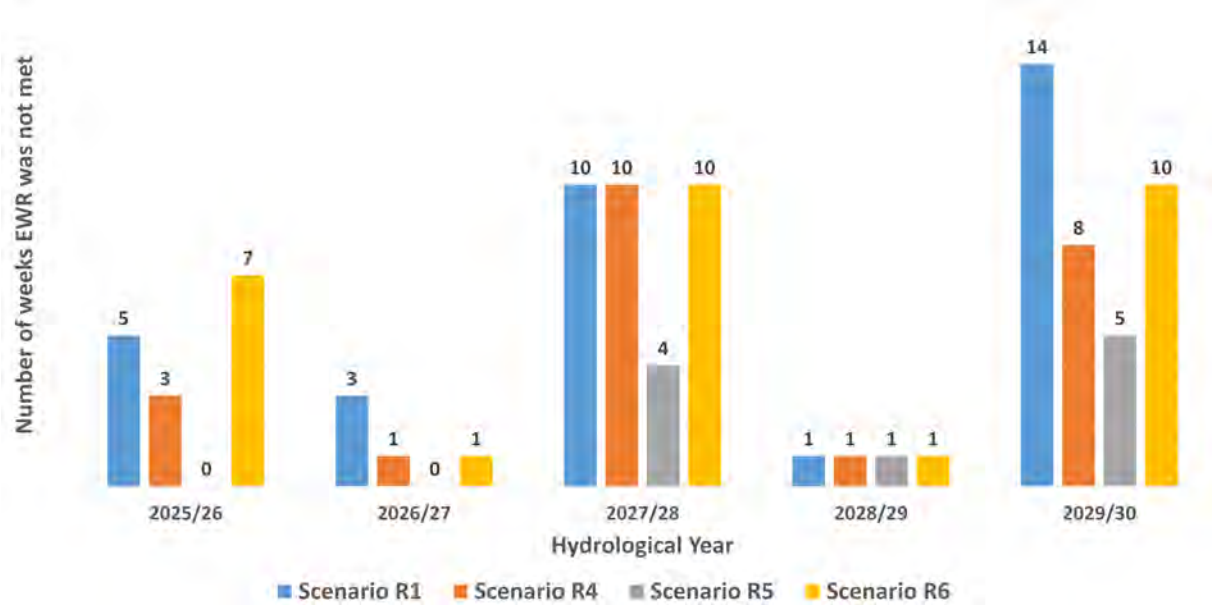

Figure 6.16: Comparison of the river flow augmentation strategies.

The scenario with the highest water stress was Scenario R3 because of the increased hectarage of the main crops of the upstream Farms, which increased their water demand. Interestingly, the water stress shown in Scenario R6 is higher than in Scenario R1. This is because the water releases made by the Farm agents releasing water in the dry period resulted in the Farms having water shortages, contributing to the average catchment water stress.

6.4.3 Comparison of measures to augment river flow

Figure 6.16 compares the river flow augmentation strategies based on the number of weeks EWR was not met in each hydrological year from October 2025 to September 2030. The graph shows that overall, having water releases helps to maintain EWR flows; however, some strategies are better than others. It can be seen that Scenario R5 had the lowest number of weeks where EWR was not met except for the year 2028/29. This is because Farms without access to the shared dam had more storage, and the shared dam had higher capacity than in Scenario R4, meaning that the WUA agent could store and release more water for EWR and the Farms without access to the shared dam could store more water, especially during winter for use the in summer thus reducing the volume of water they pumped from the river during the dry period.

Although Scenarios R1, R4 and R5 show the same number of weeks that EWR was not met for the 2027/28 hydrological year, the streamflow at the outlet was higher in scenarios with water

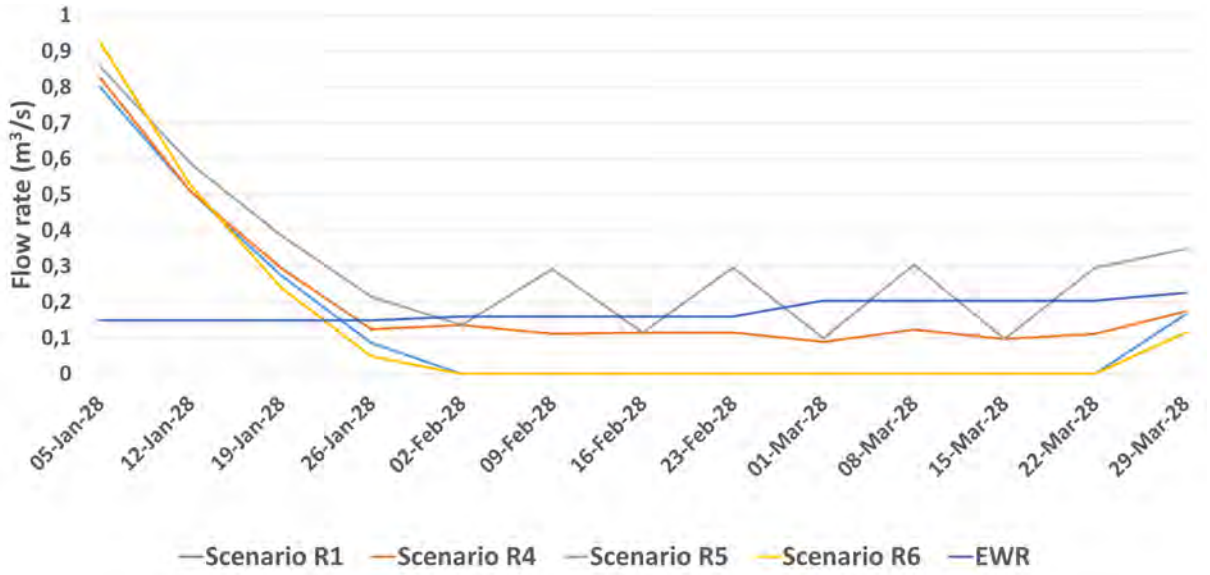

Figure 6.17: Comparison of the river flow augmentation strategies using streamflow rate at the catchment outlet from January to April 2028.

releases than in the Baseline scenario R1. Figure 6.17 shows a graph comparing the river flow augmentation strategies for a very dry period from January to April 2028. It can be seen that at the beginning of January, Scenario R6 had the highest flow rate. From 26 January to 29 March, only Scenario R5 had weeks where EWR was met. The erratic flow rate pattern of Scenario R5 was because, as described in Section 6.3.4, the WUA agent doubles the volume it releases for EWR if the EWR was not met in the previous week. Although the WUA agent exhibited the same behaviour as in Scenario R4, the flow rate was always below the EWR level because it released a lower volume than that released in Scenario R5 because of the smaller shared dam. However, even though Scenario R4 did not satisfy the EWR in this period, it had a higher flow rate than Scenarios R1 and R6.

6.4.4 Similarity to previous research

The results obtained under Scenario R1 and Scenario R2 showed that for 2025 to 2030, there was higher water availability under Scenario R2 than Scenario R1, whilst for 2055 to 2060, Scenario R1 had higher water availability than Scenario R2. This has been demonstrated by Pachauri *et al.* (2014), who showed that in the near future, the difference in precipitation and temperature between RCP 4.5 and RCP 8.5 is small but great for the far future. The low water available trend under Scenario R2 for 2055 to 2060 is similar to the results reported

by Gumbo and Kapangaziwiri (2021). The increase in the average catchment stress observed in Scenario R2 mirrors the results from the study by Becu *et al.* (2003) where some Farmers increased their water usage, resulting in more Farmers performing poorly economically. Becu *et al.* (2003) demonstrated that water availability influenced each Farmer's cash, with upstream Farmers having more cash than downstream farmers. The results of this study show a similar pattern, where Farms with higher water availability had less stress than Farms with lower water availability. The improvement in Farm water availability observed in Scenarios R4 and R5 is similar to the finding by Khan *et al.* (2017), where they discovered that water releases can increase yield. Counterintuitively, Scenario R6 showed an increase in the number of weeks where EWR was not met in one of the years simulated, even though water was being released for the environment. This is similar to the finding by Khan *et al.* (2017) that water releases migh result in lower river flow.

6.5 Chapter summary

This chapter presented the results of various future scenarios explored using the KBV ABM. Scenario R1 showed the future projection using moderate climate change data, and Scenario R2 showed future projection using extreme climate change projections. We explored various additional scenarios using RCP 4.5. The results showed that an increase of 20% in the main crops' hectarage by upstream farms would slightly increase peak average catchment stress. Various water release scenarios were explored. Scenario R5 showed that increasing dam capacities by 20% and adding a shared dam with a capacity of 2 189 25 m^3 would result in the highest water availability for farms and fewer weeks where EWR was not met. Scenario R4, similar to Scenario R5, performed better than the baseline (Scenario R1) and Scenario R6. Scenario R6 increased average catchment water stress, but there was a decrease in the number of days the EWR was not met. The results show that the KBV ABM can show results at the farm and catchment levels and can be used to explore various scenarios, making it a valuable DST.

7

Conclusion and Future Work

This chapter summarises the work done and highlights the contributions thereof. It concludes with suggestions for future research.

7.1 Summary of the study

This study aimed to co-create an ABM with KBV stakeholders that can be used as a DST for equitable and sustainable water usage in the KBV. The study used the ComMod methodology because it has been used in many SES studies to foster natural resource management discussions amongst stakeholders. Multiple workshops were held with the stakeholders at various stages of the study. During the first workshop, the ARDI process was carried out, which provided information about the actors, processes and interactions in the KBV. Information from this workshop was used to develop the conceptual model, which was validated in the second workshop. A survey was carried out at the second workshop, where more information was gathered on the stakeholders' water usage strategies, which were used in developing the KBV ABM. Model validation and exploration of future scenarios were done in the third workshop.

We expected that using ComMod would allow stakeholders to be more invested in water management discussions. Many stakeholders were invested in the water management discussions, but not all participated. Additionally, some questionnaire responses did not have answers for some questions, which added to the uncertainty in the KBV ABM.

Verification and validation were performed on the KBV ABM. The main verification process involved checking the water balance of the model. Validation was done using information obtained from the stakeholder survey, through consultations with the catchment coordinator, and

from stakeholder feedback during the workshops. The conceptual model was validated in the second workshop. Crop water demand in the KBV ABM was checked using survey results. The results of a model simulation run from 1 October 2017 to 30 September 2018 were shared with the catchment coordinator to see if they were realistic. Results from future scenarios were also shared with the stakeholders during the third workshop. These were favourably received.

7.2 Conclusion

This study has shown that the KBV ABM was co-developed with stakeholders using the ComMod methodology, which assisted stakeholders in creating a shared representation of the catchment. The involvement of stakeholders in the development of the model allowed the stakeholders to provide input, thus improving the model's credibility. The KBV ABM was coupled with SWAT, which enhanced the model's hydrological predictions by providing rainfall and streamflow data.

The different simulation scenarios demonstrate that the model can be used as a DST. The simulation results offer insights for stakeholders, especially in planning for future water management under varying climate conditions. Simulating the impact of increased dam capacities, shared water resources, and changing agricultural practices provides important information to guide policy decisions and on-farm adaptations in the KBV catchment.

7.3 Contributions of the research

The three research objectives included:

- Developing a generalisable and realistic ABM for the KBV region through collaboration with the farmers and other stakeholders in the KBV region.
- Providing a DST that could assist in developing a water management plan at a later stage.
- Investigating how climate variability affects water availability and providing relevant information to enable the creation of strategies for use by farmers in combating the problem.

This study met all the objectives. The KBV ABM was created in collaboration with the KBV stakeholders. The KBV ABM is generalisable as it can be configured for any catchment. Some design choices were also made to allow for easier future model expansion. The model can be used as a DST, as demonstrated through the future scenarios explored. Climate change impacts on the catchment were explored using RCP 4.5 for moderate climate change and RCP 8.5 for extreme climate scenarios. RCP 4.5 was chosen as the possible future climate, and various developments such as increased hectarage, farm water releases, and the addition of a shared dam that made water releases to downstream farmers were explored. The results showed that an increase in hectarage would result in a decrease in water availability for farms. The scenarios where the shared dam made water releases and provided water for irrigation to farms had higher water availability for farms and fewer weeks where EWR was not met compared to the other scenarios. The KBV ABM can provide simulation results at both the farm and catchment levels, making it a valuable DST.

7.4 Future work

This study has some limitations that could be addressed in future work.

- One of the weaknesses is that only a single iteration of ComMod was performed. Additional iterations could be made to refine the model as done by Farolfi *et al.* (2010).
- By incorporating long-term processes such as the growing of new orchards by Farm agents, execution runs of more than five years would allow longer-term planning scenarios to be explored.
- By incorporating an economic component, economic investment for various activities, such as cultivating crops, can be included in farmer decision-making.
- Another weakness of the current model is the exclusion of groundwater. However, it is known that some farmers use groundwater in emergencies, so including this in the KBV ABM would make the results more accurate.
- Different strategies for sharing and releasing water by the WUA agent can be explored to determine the most efficient operation of a shared dam in the catchment.

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A

Research Questionnaire

Research questionnaire

Water abstraction

How many pumps do you have in the river to irrigate fields directly? Please locate.

How many weirs do you have? Do they feed into dams, or are they used to irrigate fields? Please locate.

How many dams do you have, and what are their capacities? For each dam, is it instream or off-stream?

Dam name	Capacity	Instream or Offstream

For each of your dams that are fed by pumps, at what percentage level of the dam do you start pumping water into the dam?

Dam name	Percentage level

What river conditions do you check before pumping water from the river?

Do you fill any of your dams using springs? If yes, for each scenario, what percentage is provided by the springs to fill the dams?

Scenario: Wet winter

Dam name	Percentage provided by spring

Scenario: Average winter

Dam name	Percentage provided by spring

Scenario: Dry winter

Dam name	Percentage provided by spring

For each of your pumps, what is the pumping rate (cubic meters/hour or cubic meters/second or kilowatt/hour) and energy source?

Pump name	Pumping rate	Energy source

Do you fill dams using boreholes?

- Yes
- No

Are you dependent on upstream releases?

- Yes
- No

If you are a dam owner, under which circumstances do you release water if another farmer requests water?

Under which circumstances do you request water from another farmer?

How do you choose the farmer to request water from?

How many boreholes do you have? Where are they located?

What is the pumping capacity of each borehole?

What other conditions or criteria do you check before pumping water from the river into the dam, e.g. licence, restricted periods?

Crop decisions

What type of crops do you cultivate, and what is their hectarage?

Crop	Hecterage

What is the average yield per hectare for each of the crops? (data for 2015-2020)

Under which circumstances do you cultivate or not cultivate cash crops?

When do you decide whether or not to cultivate cash crops?

Irrigation strategy

Do you monitor soil moisture and rainfall? (Please circle the relevant option)

Soil moisture monitoring	Yes/No
Rainfall monitoring	Yes/No

If yes, how do you use this information?

What types of irrigation equipment do you use?

- Spray
- Drip
- Modified drip
- Other

What is the basis of your strategy for irrigation with limited water resources?

- Allocate as much water as possible to the most important crops
- Allocate an equal percentage of the available water to each crop.
- Allocate a different percentage of the water to each crop, ensuring that all crops get some water.
  In that case, please explain the choice of these ratios.

Another strategy (please explain it)

What is your prioritisation order to irrigate crops when there is limited water in the summer period?

Priority order	1st	2nd	3rd	4th	5th
Crop					

What is your prioritisation order to irrigate crops when there is limited water in the winter period?

Priority order	1st	2nd	3rd	4th	5th
Crop					

If you had enough water, how much water would you use for irrigating crops during the following periods:

	Period					
Crop	January - February	March - April	May - June	July - August	September - October	November - December

Consider the following situations:

Situation 1: There is enough water in the river, and the dam is full
Situation 2: There is enough water in the river, and the dam is low
Situation 3: There is not enough water in the river and dam is full
Situation 4: There is not enough water in the river, and the dam is low

For a typical week in each period, at the farm level, in each of these situations, what percentage of water do you use from each water source? Assume 100% is the maximum amount of water you extract in any period.

	January - February		
Situation	River	Groundwater	Dam
Situation 1			
Situation 2			
Situation 3			
Situation 4			

	March - April		
Situation	River	Groundwater	Dam
Situation 1			
Situation 2			
Situation 3			
Situation 4			

	May - June		
Situation	River	Groundwater	Dam
Situation 1			
Situation 2			
Situation 3			
Situation 4			

	July - August		
Situation	River	Groundwater	Dam
Situation 1			
Situation 2			
Situation 3			
Situation 4			

	September - October		
Situation	River	Groundwater	Dam
Situation 1			
Situation 2			
Situation 3			
Situation 4			

	November - December		
Situation	River	Groundwater	Dam
Situation 1			
Situation 2			
Situation 3			
Situation 4			

Plans for the future

Which of the following changes might you consider implementing in the next five years?

- Planting different crops
  Please indicate the crops and the reason you chose the crops.

- Change in hectarage of your main crop
- Expanding the land under cultivation
- Reducing the land under cultivation
- Purchasing more land in the Koue Bokkeveld
- Constructing new dams
- Adding new irrigation pipelines

Other changes (Please clarify)

Is there something important that we have omitted in the conceptual model?

B

Code Listings

```
createRiverNetwork
  | coordinatesCollection pairsOfCoordinatesCollection |
  coordinatesCollection := self createCoordinatesCollection.
  pairsOfCoordinatesCollection := self createPairsOfCoordinatesCollection:
        coordinatesCollection.
  self createNetworkOfArcs: RiverSegment from: pairsOfCoordinatesCollection.
  self setValuesForEntities: RiverSegment fromFile:
        'channel_routing_table.csv'.
```

Listing B.1: createRiverNetwork() method

```
initTwee
[...]
"load and initialize the upstreamChannelFlowCollection"
  self theRiverSegments do: [:rs|rs upstreamChannelFlowCollection:(self
    initializeChannelFlowCollections: rs riverSegmentID Index: 2)].
  "load and initialize the downstreamChannelFlowCollection"
  self theRiverSegments do: [:rs|rs downstreamChannelFlowCollection:(self
    initializeChannelFlowCollections: rs riverSegmentID Index: 3)].
  self theRiverSegments do: [:rs | rs initializeLandInflowCollection].
  "the method goes through all river segments and assigns them their downstream river segments
      unless the river segment is the outlet"
  self initializeDownstreamRiverSegments.
  "order theRiverSegments according to execution number."
  self orderRiverSegments.
 [...]
```

Listing B.2: Initialisation of channel flows collections and ordering of `theRiverSegments` collection

```
step: t
  self theRiverSegments
    do:
      [:riverSegmentBeingExecuted |
      | farmToBeExecuted landInflow |
      landInflow := riverSegmentBeingExecuted weeklyInflow: t * 7 - 6.  "(t*7)-6 to get first index of the collection where the model will extract 7 values of flow rate (weekly) and return the sum"
      landInflow > 0
        ifTrue:
          [riverSegmentBeingExecuted
            riverSegmentFlowRate:
              riverSegmentBeingExecuted riverSegmentFlowRate + landInflow].
      riverSegmentBeingExecuted
      riverSegmentBeingExecuted farmExtractingWaterFromRiverSegment ~= nil
        ifTrue:
          [farmToBeExecuted := riverSegmentBeingExecuted
            farmExtractingWaterFromRiverSegment.
          farmToBeExecuted
            step: t
            waterSourceRiverSegment: riverSegmentBeingExecuted
            crop_lookup_table: self crop_lookup_table]
        ifFalse: [].  "no farm is executed if no farm is extracting water from the river segment being currently executed"
      riverSegmentBeingExecuted damSegmentIsFeeding = nil
        ifTrue:
          [self routeWaterForRiverSegmentWithoutInstreamDam:
              riverSegmentBeingExecuted]
        ifFalse:
          [self routeWaterForRiverSegmentWithInstreamDam: riverSegmentBeingExecuted]].
  self theWUAs do: [:aWUA | aWUA step].
```

Listing B.3: Model step() method

```
step: week waterSourceRiverSegment: waterSourceRiverSegment crop_lookup_table:
    crop_lookup_table
  [...]
    beginningOfWinter
    ifTrue: [self orderCropFields: 'winter']
    ifFalse:
      [beginningOfWaterYear
        ifTrue:
          [self orderCropFields: 'summer'. "beginning of water year same as beginning of
    summer"
           self resetFarmAndCropFieldIndicators]
        ifFalse:
          [beginningOfNewSeason | (week = 1) ifTrue: [self makeCropDecisions]]].
  self pumpToDamsForStorage: waterSourceRiverSegment WULVolume: WULVolume.
  self updateTotalVolumeBeforeIrrigation.
  totalRainfall := self weeklyRainfall: week * 7 - 6.  "get amount of rainfall that the farm
    had during the week"
  effectiveRainfall := totalRainfall * 0.7. " not all rain water can be used by crops"
  self collectionOfFields
    do: [:aField | aField updateWeekRainfallReceived: effectiveRainfall].
  self collectionOfFields
    do:
      [:aField |
      aField updateWeekIrrigationWaterDemand: crop_lookup_table
        effectiveRainfall: effectiveRainfall].
  self updateRainfallDuringWeek.
  self updateTotalFarmWaterDemand.
  self updateWaterExpectation: effectiveRainfall.
  self irrigationWaterSource = 'dam'
    ifTrue: [thereIsEnoughWater := self checkIfDamsHaveEnoughWater]
    ifFalse:
      [thereIsEnoughWater := self checkIfRiverSegmentHasEnoughWater:
          waterSourceRiverSegment].  "check if there is a need to prioritise crops due to
    shortage of water"
  self irrigateCropsAfterSortingFields: season WULVolume: WULVolume
    waterSourceRiverSegment: waterSourceRiverSegment effectiveRainfall:
      effectiveRainfall thereIsEnoughWater: thereIsEnoughWater.
  self updateTotalFarmDamWaterStorage
```

Listing B.4: step() method for `Farm` agents

```
createFarms
  | fakeFarm |
  self loadAttribute: #farmID fromASCFile: 'Farms_200m.txt'.
  self createFragmentedEntities: Farm from: Cell attribute: #farmID.
  fakeFarm := nil.
  self theFarms do: [:f | f farmID = 0 ifTrue: [fakeFarm := f]].
  fakeFarm delete.
  self theFarms
    do:
      [:f |
      | cellsCollection |
      cellsCollection := f getEpidermis.
      f farmId: (cellsCollection at: 1) farmID].  "set farmIds"
  self setValuesForEntities: Farm fromFile: 'farms_data.csv'
```

Listing B.5: Initialisation of `Farm` agents

```
calculateFractionOfVegetableHectarageToCultivate
  | fractionOfFieldAreaToCultivate rainfallThresholdForFullCultivation totalStorageCapacity
    totalVolume |
  totalVolume := 0.
  totalStorageCapacity := 0.
  rainfallThresholdForFullCultivation := self currentSimulation
    rainfallThresholdForFullVegetableCropCultivation.
  fractionOfFieldAreaToCultivate := 0.
  self waterExpectation >= rainfallThresholdForFullCultivation
    ifTrue: [fractionOfFieldAreaToCultivate := 1.
        ↑ fractionOfFieldAreaToCultivate]
    ifFalse:
      [self collectionOfDams size = 0
                ifTrue:[fractionOfFieldAreaToCultivate := self waterExpectation /
                    rainfallThresholdForFullCultivation min: 1 ]
                ifFalse:[totalStorageCapacity := self collectionOfDams
                            inject: 0
                            into: [:sum :aDam | sum + aDam damStorageCapacity].
                        self collectionOfDams do: [:aDam | totalVolume := totalVolume + aDam
    damCurrentWaterVolume].
                        "fractionOfFieldAreaToCultivate is calculated as the ratio between
    expected rainfall and rainfall required for full cultivation for farms without dams. For
    those with dams it is a ratio of volume and capacity"
                         fractionOfFieldAreaToCultivate := totalVolume/totalStorageCapacity]].
  ↑fractionOfFieldAreaToCultivate.
```

Listing B.6: Determining fraction of vegetable fields' area to cultivate

```
irrigateWhenThereIsEnoughWater: aField waterSourceRiverSegment: waterSourceRiverSegment
    damToBeUsedForIrrigation: damToBeUsedForIrrigation WULVolume: WULVolume
  | volumeOfWaterToBeProvided irrigationWaterProvided |
  volumeOfWaterToBeProvided := aField weekIrrigationWaterDemand.
  self irrigationWaterSource = 'dam'
    ifTrue:
      [irrigationWaterProvided := volumeOfWaterToBeProvided.  "There is enough water for
    irrigation from designated source, so no need to check the volume of water the source can
    provide"
      self irrigateUsingDam: aField volumeOfWaterToBeProvided:
          volumeOfWaterToBeProvided Dam: damToBeUsedForIrrigation]
    ifFalse:
      [irrigationWaterProvided := waterSourceRiverSegment
        calculateVolumeOfWaterTheRiverSegmentCanProvide:
          volumeOfWaterToBeProvided
        WULVolume: WULVolume
        waterUsedDuringQuarterSoFar: self waterUsedDuringQuarterSoFar.
      self irrigateUsingRiver: aField volumeOfWaterToBeProvided:
          irrigationWaterProvided waterSourceRiverSegment:
          waterSourceRiverSegment].
  ↑ irrigationWaterProvided
```

Listing B.7: irrigateWhenThereIsEnoughWater() method

```
irrigateWhenThereIsNotEnoughWater: aField waterSourceRiverSegment: waterSourceRiverSegment
    damToBeUsedForIrrigation: damToBeUsedForIrrigation WULVolume: WULVolume cropPriority:
    cropPriority fractionOfWaterDemandToBeProvided: fractionOfWaterDemandToBeProvided
  | volumeOfWaterToBeProvided irrigationWaterProvided |
  volumeOfWaterToBeProvided := aField weekIrrigationWaterDemand *
      fractionOfWaterDemandToBeProvided. "lower priority crops get a fraction of their
    irrigation demand when there is shortage (fraction set in farms_data.csv)"
  ((cropPriority = 1 or: [cropPriority = 2]))
    ifTrue:
      [self irrigationWaterSource = 'dam'
        ifTrue:
          [irrigationWaterProvided := self irrigateHighPriorityCropUsingDams: aField
            volumeOfWaterToBeProvided: volumeOfWaterToBeProvided  "priority 1 and 2 crops can
    obtain  irrigation water from multiple dams when there is shortage"]
        ifFalse:
          [irrigationWaterProvided := waterSourceRiverSegment
            calculateVolumeOfWaterTheRiverSegmentCanProvide:
              volumeOfWaterToBeProvided
            WULVolume: WULVolume
            waterUsedDuringQuarterSoFar: self waterUsedDuringQuarterSoFar.
          self irrigateUsingRiver: aField volumeOfWaterToBeProvided:
              irrigationWaterProvided waterSourceRiverSegment:
              waterSourceRiverSegment]]
    [...]
  ↑irrigationWaterProvided
```

Listing B.8: irrigateWhenThereIsNotEnoughWater() method

```
createDams
  self createInstancesFromClass: Dam fromFile: 'dams.csv'.
        self setValuesForEntities: Dam fromFile: 'dams.csv'.
  self theDams
    do:
      [:d | d isMovedTo:
          (self theCells
            at:
              (d cormasX asInteger + ((d cormasY asInteger - 1) * self gridSize x))
                asInteger)].
```

Listing B.9: Initialisation of `Dam` agents

```
updateWeekIrrigationWaterDemand: effectiveRainfall
  | fieldWaterDemand fieldIrrigationWaterDemand fieldWaterDemandInMM
    adjustedIrrigationWaterDemand weekNumber|
  weekNumber := self currentSimulation timeStep.
  fieldWaterDemandInMM := (self currentSimulation
    getCrop: self cropType asSymbol
    needFor: (weekNumber - 1) \\ 52 + 1).  "(((timeStep - 1) \\ 52) +1) is to keep the key
    being searched between 1 and 52 inclusive"
    fieldWaterDemand := fieldWaterDemandInMM * 10 * self cultivatedArea.
  (self category = (#deciduous asString) or: [self category = (#citrus asString)])
    ifTrue:
      [fieldIrrigationWaterDemand := ((fieldWaterDemandInMM - effectiveRainfall) max:0) * 10 *
     self cultivatedArea.
      self weekWaterDemand: fieldWaterDemand.
      self weekIrrigationWaterDemand: fieldIrrigationWaterDemand]
    ifFalse:
      [fieldIrrigationWaterDemand := (fieldWaterDemandInMM - effectiveRainfall max:
          0) * 10 * self cultivatedArea.
      adjustedIrrigationWaterDemand := fieldIrrigationWaterDemand + (
    fieldIrrigationWaterDemand * 0.2)."adjustedIrrigationWaterDemand is being used for
    irrigationDemand because vagetable crops and pasture use less efficient irrigation"
      self weekWaterDemand: fieldWaterDemand.
      self weekIrrigationWaterDemand: adjustedIrrigationWaterDemand]
```

Listing B.10: updateWeekIrrigationWaterDemand() method