Multipurpose Reservoir Operation Management Using Evolutionary Optimisation Under Uncertainty in Water Demand and Supply

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Anh Hoang Nguyen

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ABSTRACT

Global freshwater resources are under more pressure due to high demand by industrial, recreational, municipal, and agricultural sectors. Additionally, higher standards of living, growing population, and climate variability have caused water shortages and are increasing conflict among water users.

Multi-purpose reservoirs play a crucial role in fulfilling water demands and minimising the risk of water shortages. However, multiple water users with different objectives under a variety of constraints result in water allocation challenges. Optimal water allocation from existing reservoirs has thus become a critical requirement for sustainable water resource management. Most reservoirs operate within an environment in which water demands and supplies have high levels of uncertainty. Therefore, it is crucial to recognise and analyse the impact of uncertainties on reservoir operations and the process of optimising water allocation. Although there are many optimisation techniques, genetic algorithm optimisation, using a population-based algorithm, offers a well-established and effective method for solving multi-objective problems.

This research aims to assess the water supply reliability of multi-purpose reservoirs over various operational time frames using genetic algorithm optimisation under uncertainty in climate change, land use and water demands. To achieve this aim, a thorough literature review of optimisation models, uncertainty, climate and land use change, and the application of the SWAT (Soil & Water Assessment Tool) model was conducted. A modelling framework that couples the SWAT model and the @RISK genetic algorithms optimisation tool was developed and applied to the case study of the Nuicoc watershed reservoir system in the north of Vietnam. The SWAT model, a well-known catchment model that is built to quantify and predict the effects of land management on water resources under varying climate, land use and management conditions over time, was used to simulate reservoir inflow uncertainty. Water allocation optimisation was then carried out using a probabilistic optimisation approach and genetic algorithm for various scenarios of changes in land use, climate, and water demands. The specific objectives of the case study were to (i) assess the impact of climate and land use change on water and sediment inflow into the reservoir using the SWAT model, (ii) use the probabilistic optimisation approach to compute the range of reliability, resilience and vulnerability of the reservoir under land use and climate change scenarios and (iii) suggest water

allocation policies and best management practices to improve the performance of the reservoir to sustainably supply water.

Climate data and water demands were initially kept the same as historical data to consider the impact of land-use changes on the reservoir reliability. The modelling results indicated that an expansion of the urban areas by 10% and conversion of 5% of forest to agricultural areas yielded the highest water releases for downstream demands of all simulated scenarios, with 5 Mcm/year greater water releases than the baseline, thereby not considering sedimentation. However, when sedimentation was considered, it resulted in the greatest decrease in water releases, with 6.25 Mcm/year less than the baseline. Additionally, it was found that the spatial distribution of land-use significantly affected sediment inflows into the reservoir, highlighting the importance of targeted sediment management.

Furthermore, the results showed that land use and climate change combined impacted streamflow and sediment yield from the watershed, thereby negatively affecting the reliability of the reservoir. A 10% increase in urban areas and conversion of 5% of the forest to agricultural areas under the Global Climate Model (GCM) GFDL-CM3 and Representative Concentration Pathway (RCP) 8.5 produced the highest average water inflows, at 24.72 m^3/s. This scenario, however, generated the lowest reliability and resilience of all scenarios (10% and 30% lower than the baseline, respectively), and highest vulnerability (4 lower than the baseline) due to a 114.8 million cubic metres increase in reservoir sedimentation, which may also cause greater downstream flood risk in the wet season. Modifying the water allocation policies and application of targeted best management practice (BMP) increased reservoir performance. The results indicated that implementing BMP's helped to mitigate soil erosion and increased the reliability and resilience by up to 2.7% and 9.5%, respectively, compared with the cases without BMP's. This highlights the importance of BMP's for improving reservoir performance, as sedimentation has a major long-term influence on reservoir water supply. The proposed framework was demonstrated to be useful for decision-makers in assessing the impact of water allocation policy, BMP's, land-use and climate change on the reservoir operation. The results obtained from the case study are valuable to decision makers for management of water demands, land use and sedimentation under a broad range of uncertainties. Furthermore, simulation of scenarios can help the government to formulate clearer policies to adapt and mitigate the impact of land use and climate change on the reliability, resilience, and vulnerability of the reservoir water supply.

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Name: *Thomas A. Cochrane* Signature: Date: *27/05/2021*

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GLOSARY OF TERMS

95PPU	95% probability distributions
ACO	Ant Colony Optimisation
ASABE	American Society of Agricultural and Biological Engineers
BL	Baseline
BMP	Best management practice
DEM	Digital Elevation Model
EAs	Evolutionary Algorithms
ET	The evapotranspiration
FAO	Food and Agriculture Organization
GA	Genetic algorithms
GCM	Global Climate Model
HEC-ResPRM	US Army Corps of Engineer's Reservoir Evaluation System Perspective Reservoir Model
HRU	Hydrologic Response Unit
LCM	The Land Change Modeler
LULC	Land use, land cover
M	Median
Mcm	Million cubic metres
MCS	Monte Carlo Simulation
MODIS	Moderate Resolution Imaging Spectroradiometer satellite
MUSLE	the Modified Universal Soil Loss Equation
NoSED	Sedimentation not considered
NS	Nash-Sutcliffe efficiency
PBIAS	Percent bias
PET	Potential evapotranspiration
PSO	Particle Swarm Optimisation
RCP	Representative Concentration Pathway
RRV	Reliability, Resilience and Vulnerability
SD	Standard deviation
SimCLIM	The Simulator of Climate Change Risks and Adaptation Initiatives
SUFI-2	Sequential Uncertainty Fitting Algorithm - Version 2
SWAT	The Soil and Water Assessment Tool
SWAT-CUP	SWAT Calibration and Uncertainty Programs

Chapter 1 . INTRODUCTION

1.1. Background

The available global freshwater resources are under more pressure due to higher demands by industrial, recreational, municipal, and agricultural sectors. Population growth (Figure 1.1) and higher standards of living in many areas are a main driver of this demand. Additionally, changes in land management and climate change have considerably increased pressure on water supply. Thus water demand and supply problems may subsequently raise the risk of instability and regional tensions (Global Water Security, 2012).

Effective management of water resources is thus becoming one of the most important global challenges. Effective management must be considered carefully with a wide range of constraints and priorities. In addition, participation of engineering, scientific specialists as well as other stakeholders should be promoted in effective water management (Goodarzi et al., 2013).

Reservoirs are one of the most efficient types of structures used to manage water resources for multi-purposes (Guo et al., 2004). Nevertheless, different objectives of many water users result in complicated problems in water allocation as there are a variety of constraints that need to be met. Additionally, reservoir's performance indices, uncertainties in water demand and supply, and factors of equity, reliability, and social acceptability need to be incorporated for analysis of different water allocation rules (Dinar et al., 1997; Goodarzi et al., 2013; Joshi et al., 2010).

Optimal reservoirs management is crucial for decision makers because they are greatly interested in knowing when and how they must update the water allocation rules, especially the withdrawal ratios from reservoirs to fulfil the current water demands while maximizing the benefits (Goodarzi, 2013). Currently, most reservoirs are operating within an environment in which change and uncertainty cannot always be predicted. Water demands and supplies are always under uncertainty in both the short- term and long-term while objectives tend to change over time. Additionally, many model parameters used to anticipate the hydrologic, economic, environmental, ecological and social impacts are also uncertain (Loucks et al., 2017).

Hence, it is crucial to understand the sources of uncertainty and know how to analyse and cope with the risks that arise due to these uncertainties (WWAP, 2012). According to

Maier et al. (2014), one general source of uncertainty comes from imperfect knowledge of future water demand related to population growth, agricultural needs, and urbanization. There may be unknown water availability at sources and uncertain reservoir inflow due to climate change or changes in land use or area of vegetation in reservoir basins. Another important source of uncertainty deals with changing system dynamic including the uncertain stage storage characteristics of reservoirs due to sedimentation. Other uncertainties exist as future directions of socio-economic development and legal framework (Maier et al., 2014).

Although different approaches have been expanded to measure uncertainty, management of water resource systems are still carried out without considering uncertainty analysis intensively (Goodarzi, 2013). There are a few main sources of uncertainty, such as climate change and reservoir inflow, which have been identified and described in water resource management (Maier et al. (2014). The selected uncertainties are sometimes modelled in a simplified way, without necessary consideration of spatial and temporal correlations, in spite of the fact that these have important possible impacts on water management (Maier et al., 2016).

In the field of optimising multi-purpose reservoir operation management, evolutionary algorithms are well-known and potentially efficient methods for dealing with multi-objective and nonlinear problems. Many studies have focused on optimal reservoir operation using evolutionary algorithms to assess water supply reliability. However, these studies using the deterministic approach have been conducted without considering uncertainties or only a few uncertainties such as climate change over the operational timeframe. In a deterministic approach, single values are used, probably leading to poor decisions because it is implied that there is only one possible scenario. Therefore, a probabilistic approach should be used to provide decision makers the possible range of water supply reliability of reservoirs. In addition, land use changes in the catchment of reservoirs should be considered in optimisation process because it also has considerable impacts on water supply of reservoirs. The evaluation of future water resources have to take into consideration the changes in land cover in the catchment of a reservoir, particularly in environments where water is scarce (Gallart et al., 2003) .

A framework should also be developed for quantifying the reliability of water supply of reservoirs under uncertainty in climate change, land use and water demands. Such a framework would help decision-makers assess the water supply reliability of reservoirs

across a country or a region, and would be useful for decision-makers in the management, planning, or upgrading of reservoirs.

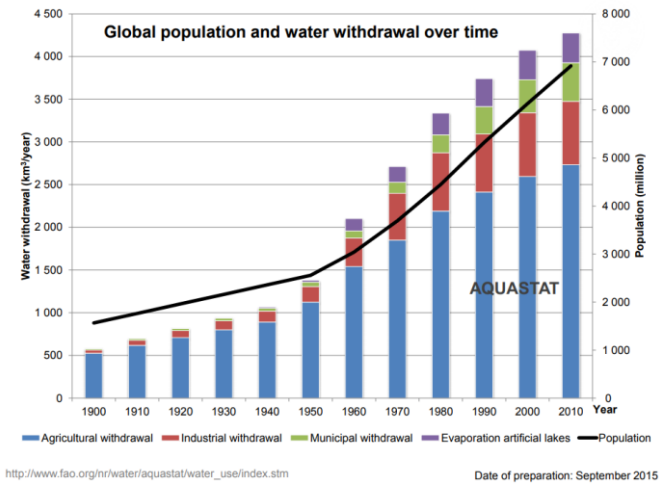


Figure 1.1. Global population and water withdrawal over time *(FAO, 2016).*

1.2. Objectives

This research will develop a framework to assess the water supply reliability of multi-purpose reservoirs over various operational time frames using evolutionary optimisation under uncertainty in climate change, land use and water demands.

The following research questions will be addressed:

1. How does uncertainty in climate change, land use and water demands affect the water supply reliability of a multi-purpose reservoir?

   Changes in future climate, land use and water demands can be substantial. This study intends to analyse and assess impacts of these changes on water supply to users.

2. What water allocation policies and best management practices can be effectively applied for a reservoir to fulfil the water demands under uncertainty?

   A reservoir may not be able to provide water for all demands simultaneously and thus reservoir operators have to consider the appropriate management policy based on downstream demand priorities. Different water allocation policies will be considered through the optimisation process to fulfil downstream demands. In addition, as land use and climate change alter water and sediment inflows into a reservoir, the application of best management practices needs to be considered to mitigate soil erosion and reservoir sedimentation to increase reservoir water supply.

In order to answer the research questions, the following tasks will be undertaken:

- An extensive literature review of optimisation methods, uncertainty, climate and land use change, water supply reliability of reservoirs.
- Development of a SWAT model to generate inflows into a reservoir based on climate and land use data.
- Development of an optimisation model under uncertainty using an evolutionary algorithm.
- Conducting statistical analysis on model inputs, including water and sediment inflows into reservoirs and water demands in a selected case study.
- Running the optimisation model with various scenarios of climate change, land use and water demands to obtain a possible range of water supply reliability under management policies.

1.3. Thesis outline

The thesis chapters following the introduction are described below.

- Chapter 2 provides a literature reviews related to this study, starting with background on reviewing optimisation algorithms in multi-purpose reservoir operation management, uncertainty analysis and optimisation under uncertainty in water resources, reservoir indicators used for performance evaluation.

- Chapter 3 presents a framework to assess the reliability of a multi-purpose reservoir under uncertainty in land use.

- In Chapter 4, the developed framework is applied to assess the impact of uncertainty in land use and climate change on future reliability, resilience, and vulnerability of a multi-purpose reservoir.

- Chapter 5 considers water allocation policy and best management practices to improve the reliability, resilience and vulnerability of a multi-purpose reservoir.

- Chapter 6 presents the final conclusions and recommendations for future research.

Chapter 2 . LITERATURE REVIEW

This literature review consists of four parts. The first part presents the origin of Evolutionary Algorithms (EAs) and critically review papers related to optimisation for reservoir operation management. The second part presents a comparison between EAs, traditional methods and other metaheuristic methods to determine the advantage of EAs in solving non-linear problems. The third part reviews the main approaches for optimisation under uncertainty. The fourth part covers water supply reliability indicators and summarizes the knowledge gaps.

2.1. Evolutionary optimisation in multi-purpose reservoir operation management

"Optimisation is the process of adjusting the inputs to or characteristics of a device, mathematical process, or experiment to find the minimum or maximum output or result" (Haupt et al., 2004). Most optimisation problems in water resources are naturally multi-objective and usually nonlinear (Deb, 2001). Metaheuristic methods are thus popular tools to resolve complex engineering problems. Metaheuristic methods include "nature-inspired optimisation algorithms such as Evolutionary Algorithms (EAs), Swarm Intelligence comprising Ant Colony Optimisation (ACO) and Particle Swarm Optimisation (PSO)" (Rani et al., 2013). In the area of water resources management, Metaheuristics have been applied extensively for many different purposes (Maier et al., 2014). EAs, which use operators inspired by natural genetic variation and natural selection, are widely well-known class of metaheuristics (Nicklow et al., 2010).

Genetic algorithms (GA) are one class of EAs. The other algorithms are evolution strategies (ESs) and evolutionary programming (EP). GA's have become the most popular because they provide a simple framework and generate higher quality solutions for complex problems (Jones, 2002).

With regards to multi-purpose reservoir operation, different optimisation models have been applied for water allocation. A study in Iran developed an optimisation model using linear programming. The model analysed different management strategies for 21 years under conditions of water deficit (Goodarzi et al., 2014). The objective was to determine monthly operating policies for the Doroudzan reservoir. The reservoir performance index, which is water supply reliability, was considered for each management strategy. The output proved that the applied methods could efficiently optimise the current operational policy of an existing reservoir. An example application of optimisation of the hydropower

operation was carried out at the Tekeze reservoir in the context of climate change (Abera et al., 2018). The Soil and Water Assessment Tool (SWAT) model and HEC-ResPRM (US Army Corps of Engineer's Reservoir Evaluation System Perspective Reservoir Model) were combined to optimise water release for hydropower considering impacts of climate change. They applied SWAT to model water inflow into the reservoir under present and future climate scenarios. The hydropower release was optimised by using HEC-ResPRM, a reservoir operation optimisation model with linear programming. Their results showed that climate change has an significant impact on inflow and hydropower production, and the optimisation model can be used to increase Tekeze reservoir power outputs by up to 30%. Since water resources optimisation are usually non-linear problems and have complicated search space, the evolutionary algorithm, which performs well with non-linear problems, has been widely used (Maier et al., 2014; Nicklow et al., 2010). For example, a reservoir operation model was designed using GA to obtain the optimum operation rule for the Dautieng reservoir in Vietnam (Ngoc et al., 2014). The model performance was assessed by the shortage index of water demand. It was concluded that GA was an effective tool for searching optimal strategy for multi-purpose reservoir operations. Similarly, the application of genetic algorithm to obtain optimal operating rules for a multi-purpose reservoir was introduced by using Pareto front where each single point on the front represents a different trade-off between possibly conflicting objectives (Reddy et al., 2006). Reddy et al. (2006) showed the optimisation model would provide many different policies for the reservoir administrators and proved the effectiveness of GA for solving multi-objective optimisation problem. A GA model to optimise the operation of multi-purpose Jiroft reservoir in Iran was also developed (Hashemi et al., 2008). The study considered probability of inflow for 12 months through scenarios of inflow probabilities from 50% to 90%. The authors claimed that through the application of the optimisation model, the reservoir can satisfy water demands as well as controlling floods.

Although evolutionary algorithms and traditional algorithms have been applied extensively in reservoir operation management optimisation, previous studies have only focused on changes in inflows and/or climate using a deterministic approach. However, a combination between climate change and projected changes in land use is necessary to obtain water and sediment inflows to the reservoir, which are subsequently processed together with water demands to optimally allocate water. It means that the uncertainty in climate change, land use and water demands should be considered in the optimisation process to assess the water supply reliability of a reservoir.

2.2. A comparison between Evolutionary optimisation methods and other methods

A comparison between Evolutionary Algorithms and Traditional Optimisation methods is described in the Table 2.1 (Davis, 1991; Deb, 2001; Haupt et al., 2004; Maier et al., 2014; Nicklow et al., 2010).

Table 2.1. A comparison between GA and Traditional optimisation methods

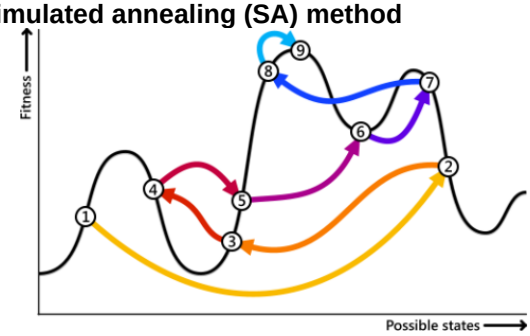
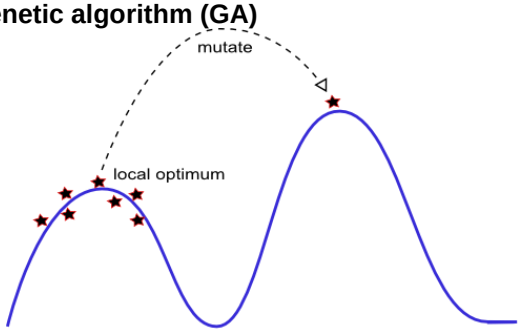
No.	Criteria	**Evolutionary Algorithms** *(Genetic Algorithm)*	**Traditional Optimisation methods**
1	Works with	Coding of parameter set	Parameters directly
2	Search style	A population of points	A single point
3	Starting point	Using multiple points randomly	Need a beginning point to start the optimisation
4	Searching rules	Probabilistic - Generating random population together with random mating, cross-over and mutation. They take longer to find solutions.	Fully deterministic. They can find the results more quickly.
5	Finding global solution	Possible to conduct both global search (i.e. exploration) and local search (i.e. exploitation) of the fitness function. Be able to escape the local optimum solution	Some methods are easy to get stuck in a local optimum solution.
6	Quality of final solution	Genetic algorithms can search multiple points at the same time. Increasing the opportunities of obtaining near-optimal solution to complicated problems.	For some methods, the quality of the final solution depends on the position of beginning point in searching space. The selection of a beginning point is very important. However, the approach of using gradient descent on a convex problem may find the global optimum.
7	Objective function	Can deal with multiple objectives.	Can solve a single objective
8	Problem types	Can solve large scale, non-linear optimisation with continuous and discrete parameters.	Difficult to deal with nonlinearities or discontinuities.
9	Simplification	Ability to solve a complicated problem without implications	Need simplifying assumptions about the problem

Traditional methods have limitations in dealing with water resources problems which are often non-linear and have complicated search space. These are overcome by Evolutionary Algorithms (Table 2.1).

In recent decades, optimisation techniques have developed and helped decision makers determine new water management and operation strategies, improve simulation models, and resolve conflicts between beneficiaries. The metaheuristic methods have become the most common method applied and are extensively used to solve complicated

problems (Boussaïd et al., 2013). Typical Metaheuristic methods can be classified into two groups (Boussaïd et al., 2013; Maier et al., 2014): Single-Solution Based and Population-Based (Table 2.2). Representatives of the Population-Based metaheuristic methods are Genetic Algorithm, Ant Colony Optimisation and Particle swarm optimisation while Simulated Annealing and its variants belong to the Single-Solution Based category (Diwekar, 2010).

Table 2.2. Classification of Metaheuristic method

Single-Solution Based	Population-Based
More exploitation (i.e. local search) (Boussaïd et al., 2013)	More exploration oriented (i.e. global search) (Boussaïd et al., 2013; Maier et al., 2014)
"Starting with a single initial solution and move away from it, describing a trajectory in the search space" (Boussaïd et al., 2013).	"Generates not a single candidate solution but a population of solutions" (Maier et al., 2014; Nicklow et al., 2010)
Simulated annealing (SA) method  SA borrowed from metallurgy. If the current solution is better than the previous one, the process continues from this new current solution. On the other hand, it is accepted under a given probability that depends on the change of Energy State (the objective function) and the current temperature (control parameter) of the process. **Tabu search (variants of SA)** "TS was designed to manage an embedded local search algorithm. It explicitly uses the history of the search, both to escape from local minima and to implement an explorative strategy. Its main characteristic is indeed based on the use of mechanisms inspired by the human memory. It takes, from this point of view, a path opposite to that of SA, which does not use memory, and thus is unable to learn from the past" (Boussaïd et al., 2013)	**Genetic algorithm (GA)**  "The genetic algorithm (GA) is an optimisation and search technique based on the principles of genetics and natural selection. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes/minimizes the "fitness" (i.e., minimizes the cost function)" (Haupt et al., 2004). **Ant colony optimisation** The implication of this method is that "Ants can find the shortest path to food by laying a pheromone (chemical) trail as they walk. Other ants follow the pheromone trail to food. Ants that happen to pick the shorter path will create a strong trail of pheromone faster than the ones choosing a longer path. Since stronger pheromone attracts ants better, more and more ants choose the shorter path until eventually all ants have found the shortest path" (Haupt et al., 2004). **Particle swarm optimisation** "The thought process behind the algorithm was inspired by the social behaviour of animals, such as bird flocking or fish schooling. PSO is similar to the continuous GA in that it begins with a random population matrix. Unlike the GA, PSO has no evolution operators such as crossover and mutation. The rows in the matrix are called particles (same as the GA chromosome). They contain the variable values and are not binary encoded. Each particle moves about the cost surface with a velocity. The particles update their

Single-Solution Based	Population-Based
	velocities and positions based on the local and global best solutions" (Haupt et al., 2004)

The capacity of finding global solutions of population-based methods is better than single-solution based methods and traditional optimisation methods (Boussaïd et al., 2013; Deb, 2001). Although, there are a number of existing population-based methods, GA's were widely applied and demonstrated to be "flexible and powerful tools in solving an array of complex water resources problems" (Nicklow et al., 2010). GA's are therefore the most appropriate tool for this thesis. A brief introduction on how GA works is described in the section below.

Optimisation using Genetic Algorithm

Genetic Algorithm's (GA), developed by Holland (1975), are search algorithms based on the mechanics of natural selection and natural genetics. Unlike conventional optimisation search methods mostly based on gradients, GA work on a population (set) of possible solutions, attempting to find a best solution set that yields extreme values (max/min) of objectives while satisfying constraints. (Loucks et al., 2017)

A set of possible solutions, which is called a population, is an array of decision- variable values. It is also defined as a set of chromosomes. Each decision variable value presented in a chromosome is called gene. There are a number of populations in a GA run and each of these populations is called generation. Population size includes a number of chromosomes. The GA process is summarized in the Figure 2.1.

Firstly, the variables, objective function, and constraints must be determined. Then the GA operator such as type of chromosome representation, population size, selection progress, types of crossover and mutation and crossover and mutation probabilities are defined by the modeller. In the next step, the initial population is generated randomly. It provides the set of possible solutions for the first generation.

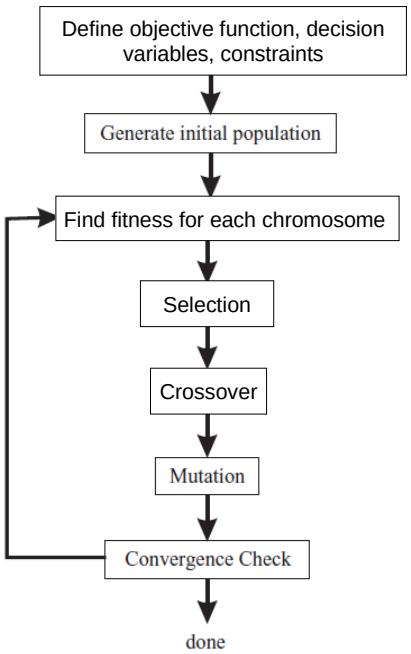


Figure 2.1. Flowchart of Genetic Algorithm (Haupt et al., 2004).

After that, the objective function is applied to assess each chromosome in the population. Each chromosome has an assigned fitness value which is used to select the chromosomes from the current population. This progress is known as *selection*.

GA operators *including crossover and mutation*, are performed on the selected chromosomes to create a new set of chromosomes that make the new population for the next generation. This algorithm is repeated sequentially until the stopping criterion is achieved. After this step, the optimum solution is obtained, satisfying all constraints. Details on GA can be found for instance in Goldberg (1989).

2.3. Uncertainty analysis and optimisation under uncertainty in water resources

Uncertainty is an important factor that decision-makers need to consider in management and operation of water systems. It should be emphasized that “Information on uncertainty does not make decision-making easier, but to ignore it is to ignore reality” (Loucks et al., 2017).

Uncertainty takes place in all aspects of water resources management optimisation. When solving real-world problems, it is crucial to consider this factor in the process of optimisation (Maier et al., 2014). It is unfeasible to completely anticipate how well any water resource systems will operate in the future. Such systems are subject to changing and uncertain inputs, and uncertain demands. The more decision-makers comprehend

these uncertainties, the better they can plan, perform and manage water systems to minimize them (WWAP, 2012).

Understanding the uncertainties requires understanding of the sources of uncertainty. Uncertainty in water resource management was classified in two basic forms (Vucetic et al., 2011). The first one caused by hydrologic or natural variability (described as stochastic variability). The key sources of variability include temporal and spatial changes. The other one caused by an underlying lack of knowledge. In another study, uncertainty was specifically considered in 5 levels (Marchau et al., 2019). Level 1 was used with deterministic modelling due to clear future (complete certainty). Level 2 was suitable for alternate futures using probabilitic approach. Regarding a few plausible futures, level 3 was suggested to apply with a few alternative models. The core of this approach is that the future can be predicted well enough through scenarios. It was implied that "a scenario does not predict what will happen in the future; rather it is a plausible description of what can happen" (Loucks et al., 2017; Marchau et al., 2019). A range of plausible futures (scenarios) can be specified well enough to identify a policy that will produce acceptable outcomes. Level 4 and 5 describe the deepest levels of uncertainty (deep uncertainty), in which we "(i) cannot quantify nor use probabilities, (ii) know there could be surprises, (iii) know neither the mechanisms, functional relationships nor statistical properties, and (iv) do not know the valuation of the outcomes" (Dierickx, 2019).

Regarding the assessment of reservoir water supply under climate and land use change, probabilistic approach is appropriate to describe the spatial and temporal change of hydrological variables (Vucetic et al., 2011) such as river flows. There have been studies considering uncertainty using probabilistic approaches in water resource management. An approach called probabilistic multiple objective genetic algorithm has been introduced (Singh et al., 2008). This approach incorporates uncertainty with multiple objective Pareto optimisation in ground water remediation design. The results demonstrates that using such an uncertainty-based multi-objective optimisation scheme can give valuable information about remediation options. In another study, reservoir operation rules optimisation under uncertainty of inflows in a long-term period were conducted by evolutionary algorithm (Soltani M.A., 2008). However only the uncertainty of inflows was considered while uncertainty in climate change, agricultural and urban water demand were ignored for all periods. Another study, used a probabilistic approach combining Monte Carlo Simulation (MCS) engine and genetic algorithm was developed to optimise the number of development wells for oil and gas companies (Al-Harthy, 2010). All input

parameters were generated randomly based on triangle distributions (max, min and median values). This generated the maximum benefit under uncertainties in well rate, capital cost and price. The results actively supported decision-making process with visualization. In Al-Harthy's study, the probabilistic simulation adjusts the deterministic simulation by using probability distributions to generate the random values for input data, as suggested by Vucetic et al. (2011).

The Monte Carlo Simulation (MCS) is regularly applied for risk analysis, particularly in the case that the input variables are uncertain. "The Monte Carlo simulation method is a powerful modelling tool for the analysis of complex systems, due to its capability of achieving a closer adherence to reality" (Zio, 2013). Through the model, a large number of random samples are applied to generate corresponding samples of outputs. As each input is random, the outcomes of a model are also random (Thomopoulos, 2012). Additionally, MCS is a highly flexible and robust method to solve a wide range of problems (Jain et al., 2008). MCS uses probability distribution including a range of values for all uncertain inputs instead of the deterministic value of parameters . There are two main concerns with MCS, including: (i) MSC needs a large number of computations to yield random values, and (ii) the accuracy of outputs strongly relies on the number of iterations and simulations. These days, two concerns have been easily dealt with by support of computers.

MCS has been applied to reservoir operation studies. Based on statistical data, MCS was used to extend historical inflow for reservoir operations from 252 to 432 months (Goodarzi et al., 2014). The synthetic inflow data was input to determine the impacts of alternative scenarios on the reservoir operation. In another study, simulation model of reservoir management was tested with 1000 sequences of synthetic data having the same length as historical data (Oskoui et al., 2015). The outcomes showed that MCS was helpful for predicting the effects of possible future changes on reservoir operations.

Uncertainty in climate and land use change is suitable to be expressed by scenarios. This uncertainty has been considered by a range of studies (Khoi et al., 2014; Pervez et al., 2015; Shrestha et al., 2018). In the field of reservoir operation management optimisation, the combination of MCS and an optimisation tool seems to be an ideal probabilistic approach for optimisation over operational timeframe. This approach will be considered under uncertainty in climate and land use change to assess the reservoir water supply. In an environment with high level of uncertainty, this approach will help to solve water

resources problems and provide decision-makers with a possible range of water supply reliability of reservoir systems.

2.4. Evaluating water resource system performance

Performance criteria are essential to assess operation periods of water resource systems (Hashimoto et al., 1982). The water supply reliability indicator for multipurpose reservoirs (Hashimoto et al., 1982; Jain et al., 2008) is described below (Equation (2.1)).

- *Reliability* is the ratio between water volume supplied over total volume demanded.

$$\alpha = \frac{V_s}{V_d} \times 100\ (\%) \tag{2.1}$$

  Where V_s is the volume of water released and V_d is the volume of water demanded in the given period.

- Water releases and water spillage from reservoir obtained from simulations are also considered.

There are a number of studies related to optimisation-based reliability of a multi-purpose reservoir (e.g., Goodarzi et al., 2013; Jain et al., 2008; Marton et al., 2014; Olukanni et al., 2018; Ziaei et al., 2012). A study evaluated different management strategies for a reservoir over 20 years by using linear optimisation model (Goodarzi et al., 2013). The water supply reliability was considered for each management strategy, forcing reservoir operators to choose the appropriate strategy based on available water and downstream priorities. Nevertheless, this study was limited, because the reliability of water supply of reservoirs should be considered under future uncertainty in climate change, land use and water demand because they are factors greatly impacting on reservoir operation.

Very few studies have been carried out to develop a framework for quantifying the reliability of water supply of reservoirs under uncertainty in climate change, land use and water demands. A framework assessing the water supply reliability of a reservoir under climate change using GA and deterministic approach was developed . However, a probabilistic approach and more uncertainties should be taken into consideration to provide decision makers a range of possible water supplies.

In conclusion, through literature review the main knowledge gaps were identified as follows:

- The impacts of uncertainty in climate change, land use and water demands have not been simultaneously taken into account in optimisation process to assess the reliability of water supply of reservoirs under different management policies.
- Multi-purpose reservoir operation management using evolutionary algorithm has not been considered under uncertainty in climate change, land use and water demands.
- A framework for quantifying the reliability of water supply of reservoirs under uncertainty in climate change, land use and water demands has not been developed for decision-making progress.

Therefore, as stated earlier, the aim of this study is to develop a framework to assess the reliability of water supply of multi-purpose reservoir under uncertainty in climate change, land use and water demands through a probabilistic approach by using an evolutionary optimisation method combined with a Monte Carlo simulation. In this study, uncertainties in future trends, including land use and climate change, are expressed by scenarios and uncertainties during operational timeframes, such as river flows and water demands, are described by the probability distributions.

Chapter 3 . A FRAMEWORK TO ASSESS THE RELIABILITY OF A MULTI-PURPOSE RESERVOIR UNDER UNCERTAINTY IN LAND USE

3.1. Introduction

Available freshwater resources in rapidly developing countries are becoming scarce due to higher demands from industrial, recreational, municipal, and agricultural sectors (Pokhrel, 2018; Ziaei et al., 2012). In addition, socio-economic developments can lead to significant changes in land-use, which can subsequently impact on water resources critical for downstream economic development (Shrestha et al., 2018). Effective management of water resources with different water use and policy constraints, in conjunction with projected land-use changes, is thus a key challenge for sustainable development (Goodarzi et al., 2013; Shrestha et al., 2018).

Reservoirs are widely used to manage water resource storage and allocation for multiple water demands (Guo et al., 2004). For example, reservoirs can be used to store water during the wet season and make it available during dry season to meet demand of various sectors. However, rapid economic development, particularly in developing countries, can result in changes in land-use and land cover (LULC) within a reservoir's watershed. Urban areas often expand due to increasing development of industrial and residential zones. In contrast, natural forest areas are often replaced for agricultural production. Urbanisation and conversion from forest to agriculture not only induce changes in evapotranspiration, surface runoff, groundwater and streamflow, which affect water supply to reservoirs, but also cause soil erosion and the transport of sediment to reservoirs, which can also have an effect on the water storage capacity and operation of a reservoir (Bieger et al., 2015; Shrestha et al., 2018). Changes in forest, urban and agricultural land-use areas in a reservoirs' watersheds can thus cause changes in the way water in a reservoir is managed (Abera et al., 2018; Shrestha et al., 2018). Consequently, assessing the impacts of future land-use change on a reservoir's water supply reliability is essential.

The impacts of LULC change on streamflow have been widely studied for a range of different regions of the world using hydrological models (Dwarakish et al., 2015; Saddique et al., 2020; Yalew et al., 2018). Although there are a wide range of hydrological models available, the Soil and Water Assessment Tool (SWAT) is widely used for assessing the impact of land-use changes on water and sediment flows because it is a well-documented model, it is freely available, and has been shown to perform well through numerous

validation studies (Choto et al., 2019; Shrestha et al., 2018; Zhang et al., 2019). As expected, most studies indicated that conversion from forest to agricultural area would generate more run-off and sediment, and that increasing urban areas can also result in greater run-off. For example, a study on the impact of LULC change on stream flows in the Sesan, Srepok, and Sekong Rivers (3S) basin of the Mekong, showed that future expansion of urban areas and rapid transformation from forest to agricultural areas could have considerable effects on streamflow and sediment loads and have an influence on the operation of reservoirs in the region (Shrestha et al., 2018). The impacts of individual land-use types on runoff and sediment yield at a sub-basin scale within Hun River basin in China were evaluated, and it was found that forest land decreased sediment yield over the year and increased water percolation, while urban land generally increased runoff and decreased sediments yield. Similarly the impacts of rapid LULC change on streamflow and sediment yield of the Gojeb watershed, Ethiopia, were evaluated and it was concluded that conversion from forest to cultivated land increased streamflow and sediment yields (Choto et al., 2019). In another study on the effect of LULC change on flow and sediment yield in the Khokana Outlet of the Bagmati River, Nepal, it was also concluded that the expansion of the urban area led to an significant increase in streamflow, whereas groundwater contribution to streamflow decreased due to decreasing urban infiltration (Pokhrel, 2018).

The optimisation of water supply from reservoirs to meet demand is also an area of intensive research (i.e. i.e. Abera et al., 2018; Ahmed et al., 2005; Anand et al., 2018; Ehteram et al., 2018; Jothiprakash et al., 2006; Sheibani et al., 2019; Ziaei et al., 2012). Genetic optimisation algorithms (GA's) are one type of the population-based methods that were demonstrated to be "flexible and powerful tools in solving an array of complex water resources problems" (Nicklow et al., 2010). GA's can solve large-scale, nonlinear problems with a large number of variables, and have the capacity of finding optimum solutions (Boussaïd et al., 2013; Haupt et al., 2004; Maier et al., 2016). Both deterministic and probabilistic GA approaches have been used to optimise water allocation. The deterministic approach provides a single output as this approach uses a single input value/signal, such as a time series of water inflows and water demands (e.g.Abera et al., 2018; Anand et al., 2018; Jothiprakash et al., 2006; Tukimat et al., 2014). Uncertain factors are not considered in this approach (e.g. water and sediment inflows, water demands). On the other hand, the probabilistic approach has been used in a number of studies to account for uncertainty (Vucetic et al., 2011). For example, an approach called

the probabilistic multiple objective genetic algorithm (Singh et al., 2008) was used to incorporate uncertainty in aquifer hydraulic conductivity values by including multiple objective Pareto optimisation in groundwater remediation design. The results demonstrated that this approach could give valuable information about remediation options. In another study, a probabilistic approach was used to optimise the number of development wells for oil and gas companies. All input parameters, expressed by probabilistic distributions, were generated randomly by Monte Carlo Simulation (MCS) (Al-Harthy, 2010). This generated the maximum benefit under uncertainties in well rate, capital cost and price. In most situations, whilst the former can provide the trend of changes, the latter can describe the range of possible output due to uncertainty other than the trend of changes. The probabilistic approach can, thus, actively support decision-making process with visualisation and more information (Al-Harthy, 2010).

Most reservoirs operate within an environment in which water demands and supplies are uncertain. Additionally, many model parameters used to anticipate the hydrologic and environmental impacts of land-use changes are also uncertain (Loucks et al., 2017). Although many researchers have studied the impact of LULC change on streamflow and sediment yields and investigated the application of various optimal reservoir operation algorithms, most of them have conducted these tasks separately. However, there are a few studies that considered the impact of LULC change on optimal reservoir operations. Optimal operation of the Tekeze reservoirs within the Eastern Nile was studied by coupling SWAT and HEC-ResPRM (Abera et al., 2018). In that study, the current land-use in the watershed, and climate change scenarios (RCP 4.5 and RCP8.5) were simulated, but sediment yield and change in LULC were neglected in their future socio-economic development scenarios. Similarly, Anand et al. (2018) optimised the reservoir operation in the Ganga River basin by combining the SWAT and a genetic optimisation algorithm. However, uncertainty in LULC, sediment yield, and water demands were also not studied.

Reservoir operators are tasked to meet water demands under current land-use; however, they also need to know how uncertainty in future land-use change will impact future operations for planning purposes. Therefore, the aim of this study is to assess how uncertainty in LULC changes and related sediment yields affect water supply reliability of reservoirs. To accomplish this aim, a reservoir water reliability assessment framework consisting of the SWAT model and an optimisation tool was presented and applied to the Nuicoc reservoir watershed in the north of Vietnam. The Nuicoc watershed-reservoir

system is of high socio-economic-environmental importance because (1) urbanisation of the watershed is quickly taking place, and conversion from forest to agriculture is increasing; (2) the Nuicoc reservoir is playing an important role in the region as it is providing water for agriculture, urban areas, environmental flows and tourism; (3) the reservoir is being burdened with growing water demands, as is the case in many rapidly developing watershed reservoir systems. The impact of uncertainty in LULC change and sediment yields to the reservoir are simulated through various development and water policy scenarios to assess the reliability of the reservoir. The specific objectives of the case study are thus to (1) assess the impact of LULC change on the water and sediment inflows into the reservoir using SWAT, (2) use a probabilistic optimisation approach to account for uncertainties in water and sediment inflows and water demands, and calculate the range of reliabilities of the reservoir under possible LULC change scenarios, and (3) compare the probabilistic approach with the deterministic approach to assess what kind of information is best suited to support the planning process. Addressing these objectives is essential for decision-makers in future reservoir planning and management.

3.2. Materials and Methods

3.2.1. The Framework

SWAT and the @RISK genetic optimisation tool (Palisade, 2016) were incorporated in a framework to determine reservoir water supply reliability under uncertainty (Figure 3.1). SWAT is used widely for river hydrology, but it does not have a capability to determine optimal water allocation for downstream water users (Ashraf et al., 2017). On the other hand, @RISK is a widely used tool for optimisation under uncertainty (Al-Harthy, 2010), but requires inflow data to perform optimisation calculations. Within the framework, a calibrated SWAT model is used to generate water and sediment inflows to a reservoir based on climate data and land-use scenarios. Simulated inflows to the reservoir and water demands from downstream users controlled by management policy are then fed into the @RISK tool to determine the reliability of water supply.

Uncertainty in SWAT simulations are considered through uncertainties in parameters, which results in a potential range of monthly inflows. To account for these water inflow uncertainties in the optimisation, separate uniform distributions for each month are utilised.

Another uncertainty factor that the framework takes into account is sediment yield, as it reduces storage capacity over time, which affects the reliability of a reservoir. Streamflow

transports sediment into the reservoir, and thus uncertainty in water inflows in turn leads to uncertainty in sediment inflows. Although sediment yields are a function of many factors (soils, land cover, etc.), the water runoff rate plays a crucial role in sediment yields. Higher water runoff as expressed as water inflows to the reservoir will generate a greater amount of sediment. Therefore, there is a close relation between water inflows and sediment inflows.

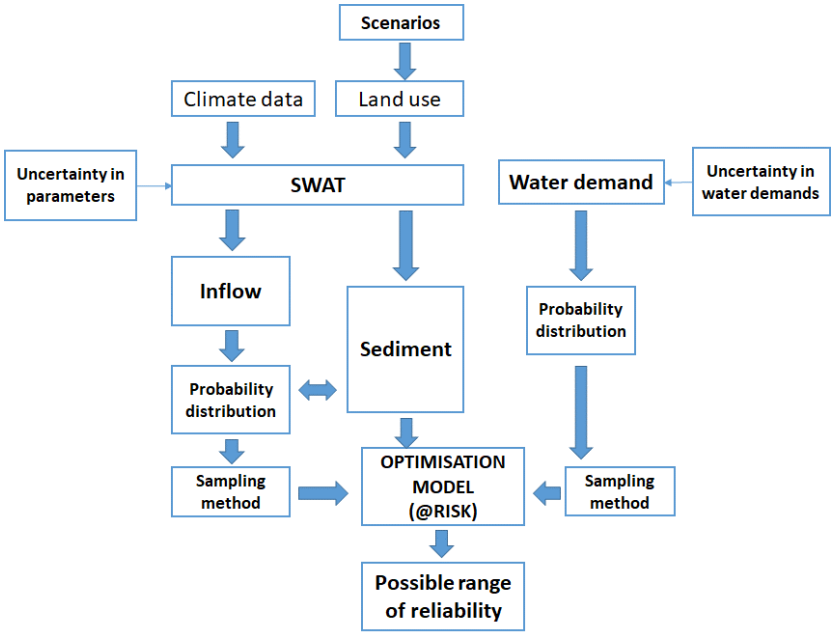


Figure 3.1. A Framework to assess the impact of land-use change on reservoir water supply reliability.

Uncertainty in water demands is also considered. During the operational period of a reservoir, monthly water demands can fluctuate. Based on monthly measured data, probability distributions of water demand were computed to incorporate uncertainty in water demands. The Latin Hypercube sampling method (Goodarzi, 2013) is then used to randomly create a number of possible combinations of water and sediment inflows and water demands as input for the optimisation model. This in turn generates a range of reservoir water supply reliabilities. Uncertainties in future trends are expressed by scenarios and uncertainties during operational timeframes which are quantified by the probability distributions. This approach results in a probabilistic assessment of water supply reliability, which is then compared with a deterministic calculation of reliability.

3.2.1.1. SWAT modelling and uncertainties

In SWAT, the watershed is divided into sub-basins, and then these are divided into Hydrologic Response Units (HRU). Each HRU is a unique combination of land-use, soil type and slope gradient. The simulation of hydrology in the watershed is carried out in

two phases. The first one is the land phase that controls the amount of water and sediment yield to the main channel in each sub-basin. This phase is based on the water balance, which is calculated for each HRU using climate, soil, topography and LULC data. Overland run-off occurs when the rate of water application to the ground surface surpasses the rate of infiltration. Sediment yield in the watershed is calculated by using the Modified Universal Soil Loss Equation (MUSLE) for each HRU (Neitsch et al., 2011). The second phase determines the routing of water and sediment through the channel network of the watershed to the outlet (Neitsch et al., 2011) . Sediment routing in the channel is managed by two processes, deposition and degradation. Deposition happens if the upland sediment load is greater than the transport capacity of the channel. This process is reversed for degradation. The transport capacity of a channel segment is calculated as a function of the peak channel velocity (Arnold et al., 1995). Management practices in SWAT are defined for each HRU, including planting, harvesting, fertiliser and pesticides applications. Crop growth is determined by a crop database providing plant parameters for a range of plants and land cover types (Neitsch et al., 2011).

SWAT-CUP (SWAT Calibration and Uncertainty Programs) is a standalone program developed for calibration of SWAT ((Abbaspour et al., 2007)). In this research, for model calibration and validation and for the determination of uncertainties, we used the program SUFI-2 (Sequential Uncertainty Fitting Algorithm - Version 2) in SWAT-CUP (Abbaspour et al., 2004; Abbaspour et al., 2007). The concept behind the algorithm of SUFI-2 is that parameters to calibrate the SWAT model (e.g. curve number or percolation fraction) in various locations of a watershed, under different land-use, can vary. To calibrate the SWAT model with the “traditional” or “deterministic” approach, the model adjusts parameters until a reasonable match between observation and simulation is reached. However, many different sets of parameter values, as a result of possible combinations among parameters, will also create a reasonable match (Abbaspour, 2013). Consequently, uncertainty in parameters significantly affect the model outputs. To consider uncertainties in parameters, SUFI-2 uses a stochastic approach to improve calibration. Uncertainties are expressed as ranges using uniform distributions. The uncertainties in the parameters leads to uncertainties in the model output variables (e.g. streamflow), which are expressed as the 95% probability distributions (95PPU) (Abbaspour, 2013) (Figure 3.2). After choosing parameters to calibrate a model, a uniform distribution is generated for each parameter, bound by the maximum and minimum values. The Latin Hypercube approach is then used to generate *n* samples for the model

to run *n* simulations. This produces *n* discharge outputs, *q*(*n*), which will subsequently be compared with observed data on the basis of an objective function (e.g. Nash-Sutcliffe efficiency NS (Nash et al., 1970) or percent bias PBIAS). All simulations, in which objective function values are higher than the threshold suggested by American Society of Agricultural and Biological Engineers (ASABE) guidelines (ASABE, 2017), are considered. The cumulative distributions of those simulations are then calculated for each month of the simulation period. The 95PPU of outputs is extracted at 2.5% and 97.5% values. Therefore, the 95PPU can represent the possible range of outputs as a result of uncertainties in parameters (Abbaspour et al., 2007).

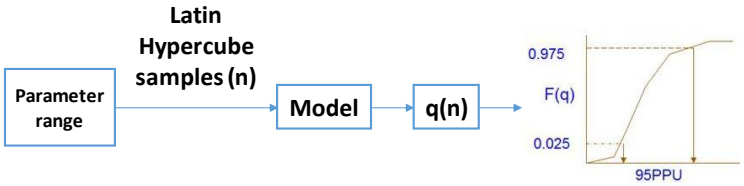


Figure 3.2. Obtaining the 95% probability distribution (95PPU) using SWAT-CUP to quantify parameter uncertainty (SWAT Group, 2020).

3.2.1.2. Optimisation tool

To optimize water releases, the genetic optimisation algorithm within @RISK was applied to minimise the sum of the squared deviations of monthly total demands and water releases (objective function). Due to uncertainty in water and sediment inflows, and water demands during the operational timeframe, a probabilistic approach was used. The probabilistic optimisation approach adjusts the deterministic approach by using probability functions to generate the random values (Al-Harthy, 2010; Vucetic et al., 2011).

Genetic Algorithms (GA), developed by Holland (1975), are search algorithms based on the mechanics of natural selection and natural genetics. GA has been used widely in studies to solve multi-objective and non-linear problems of water resources management (i.e. i.e. Ahmed et al., 2005; Anand et al., 2018; Bozorg-Haddad et al., 2018; Jothiprakash et al., 2006; Sheibani et al., 2019). The main components of this algorithm are the objective function, the population, the crossover and the mutation. GA works on a population (set) of possible solutions (decision variables), attempting to find an optimum value (maximum or minimum values) of the objective function, while satisfying constraints. A population is also defined as a set of chromosomes. Each decision variable value presented in a chromosome is called a gene. GA will take a number of generations to finalise and find the optimum solutions. Details on GA can be found for example in

Goldberg (1989). In the framework, the process of setting up the optimisation tool is briefly described as follows:

- Step 1: Determine the following key factors for the optimisation tool: (i) Objective function (Equation (3.1)), (ii) Decision variables (water releases), and (iii) Constraints (Equations 3.2-3.7). Step 2: Set up a deterministic optimisation model using monthly deterministic input data.
- Step 3: Replace monthly deterministic input data including monthly inflows, sediment values, and water demands by monthly probability distributions to include uncertainties.
- Step 4: Generate a number of random possible combinations (n = 180 was chosen for this study because it balances computational cost vs. accuracy in obtaining a reliable solution) of water inflow, sediment inflow and water demand for the optimisation model using the Latin Hypercube sampling method in @RISK. Run the genetic optimisation algorithm in @RISK for each possible combination and evaluate the possible range of reservoir reliabilities.

The main optimisation objective is to optimise total reservoir release for each sector demand (i.e. urban, agriculture, etc.) over an operational period. The objective is described by Equation (3.1) (Minimize sum of squared deviation between demands and supplies).

$$Z = \text{Minimise}\left(\sum_{i=1}^{n}\sum_{j=1}^{12}(T_{i,j} - R_{i,j})^2\right) \tag{3.1}$$

Where Z is the objective function, $R_{i,j}$ are water releases for users in month j and year i, $T_{i,j}$ are total demands (water releases cannot be greater than total demands), and n is total number of simulation years.

The constraints for this problem are:

a) Water balance continuity equation:

$$S_{i,j+1} = S_{i,j} + I_{i,j} - E_{i,j} - R_{i,j} - O_{i,j} \tag{3.2}$$

Where $S_{i,j}$ is the reservoir storage in year i, month j, $I_{i,j}$ is the reservoir inflow, $O_{i,j}$ is water spillage from the reservoir, $E_{i,j}$ is evaporation from the reservoir, and $R_{i,j}$ is water release.

b) During the operational period, reservoir storage ($S_{i,j}$) must be higher than dead storage (S_{min}) and lower than active storage (S_{max})

$$\begin{cases} S_{i,j} \leq S_{max} \\ S_{i,j} \geq S_{min} \end{cases} \tag{3.3}$$

Where $S_{i,j}$ is the reservoir storage during operation time, S_{max} is active storage, and S_{min} is dead storage.

c) Minimum reservoir storage constraints for recreation: The government requests the reservoir to keep the minimum water level at 43 m (55 Million cubic metres (Mcm)) in May for recreational purpose. Thus,

$$S_{i,5} \geq 55 \text{ Mcm} \tag{3.4}$$

d) Meeting minimum sector demand priorities: As the reservoir cannot meet all demands over the operation period, the following constraint for minimum allowable releases was implemented (as proposed by Goodarzi et al. (2013); Ziaei et al. (2012)):

$$U_{i,j} + aA_{i,j} + bD_{i,j} \leq R_{i,j} \leq U_{i,j} + A_{i,j} + D_{i,j} \tag{3.5}$$

Where $R_{i,j}$ are water releases, $U_{i,j}$ are urban demands, $A_{i,j}$ are agricultural demands, $D_{i,j}$ are downstream river demands, and a, b are priority coefficients.

The values a and b, which represent the priority coefficients for agriculture and river downstream demands, are based on government policy guided by the current economic development in the study area. In this case study, allocated priority coefficients for agricultural and downstream river demands are considered less important than urban (domestic/industrial) demands. Agricultural and river downstream demands will be sacrificed during the shortage. The reservoir provides water for the downstream river which belongs to another catchment. This river, then, supplies water for other irrigation systems. The problem of potential ongoing water shortages for agriculture will be solved by finding other available water sources or considering to change to different crop types in the future. In this study, we selected a = 50%, b = 0%.

e) Penalty function:

- Penalty function when reservoir storage is greater than active storage (P_1)

$$P_1 = \max \begin{cases} 0 & \text{if } S_{i,j+1} < S_{max} \\ \sum\sum \left(S_{i,j+1} - S_{max}\right)^2 & \text{if } S_{i,j+1} > S_{max} \end{cases} \tag{3.6}$$

- Penalty function when water release is lower than minimum allowable release (P_2)

$$P_2 = \max \begin{cases} 0 & \text{if } R_{i,j} > U_{i,j} + aA_{i,j} + bD_{i,j} \\ \sum\sum \left(\left[U_{i,j} + aA_{i,j} + bD_{i,j}\right] - R_{i,j}\right)^2 & \text{if } R_{i,j} < U_{i,j} + aA_{i,j} + bD_{i,j} \end{cases} \tag{3.7}$$

If the reservoir storage and water release do not satisfy the constraints (Equations (3.3) and (3.5)), the penalty function defined in Equations (3.6) and (3.7) are added to the objective function (Equation (3.1)) to penalise the infeasible solution.

To validate the results, a deterministic approach will be used to compare with the probabilistic approach. The deterministic approach will take the median (M95PPU) water and sediment inflows from 95PPU in SWAT-CUP and median water demands for the simulation period. The approach using median inflows in SWAT-CUP was proposed by Ashraf et al. (2017) where the median inflows to the reservoirs and net irrigation requirements were extracted from the SWAT-CUP output to examine the productivity of irrigated wheat and maize yield in the Karkheh River basin in Iran.

3.2.1.3. Model performance indicators

Performance indicators are essential to assess operation periods of water resource systems (Hashimoto et al., 1982). The water supply reliability indicator was considered in this study. According to Hashimoto et al. (1982), water supply reliability is the probability that the reservoir operates in the set of satisfactory states. The volume reliability in water supply (Equation (3.8)) was used by Jain et al. (2008) and Ehteram et al. (2018) to assess reservoir operations. Additionally, other indicators including total water releases and total water spillage were also considered. The indicators used in the study are:

1. *Volume reliability* (R_{ev}): is the ratio between water volume supplied over total volume demanded.

$$R_{ev} = \frac{V_s}{V_d} \times 100\ (\%) \tag{3.8}$$

Where V_s is the volume of water released and V_d is the volume of water demanded in the given period. This indicator will show an overview of reliability in water supply (Jain et al., 2008).

2. *Water release* (R): is the total water releases for demands downstream over an operational period.

3. *Water* spillage (WS): is the total of exceeding water spilled through the spillway.

3.2.2. Nuicoc Watershed Case Study

3.2.2.1. Watershed and reservoir

The Nuicoc watershed is located in the mountainous area of Thai Nguyen province, in the North of Vietnam (Figure 3.3). The average annual rainfall and evaporation in the 575-

km^2 watershed are estimated at 1,850 mm and 1,100 mm, respectively, while the average temperature is around 25°C. The annual average amount of rainfall in wet seasons, which often last from June to October, accounts for 75% in a given year. This watershed has a mean annual inflow of roughly 490 million cubic meters (Mcm) flowing into the reservoir. The Cong River in the Nuicoc watershed has an estimated mainstream length of 60 km.

Forests account for 52% of the area, crop cultivation for 30%, rural residential areas 9%, urban residential areas 1.2%, and other land accounts for the remaining 7.8%. Considerable socio-economic growth has led to a rapidly increasing trend in urbanisation and a quick conversion from forest areas to agricultural areas.

The reservoir has a storage capacity of 175 Mcm (the active storage), and the water surface area corresponding to the active storage is approximated at 2,460 ha. It was designed to supply water for agriculture (irrigation), urban supply, tourism, and to maintain required flows for a downstream river nearby.

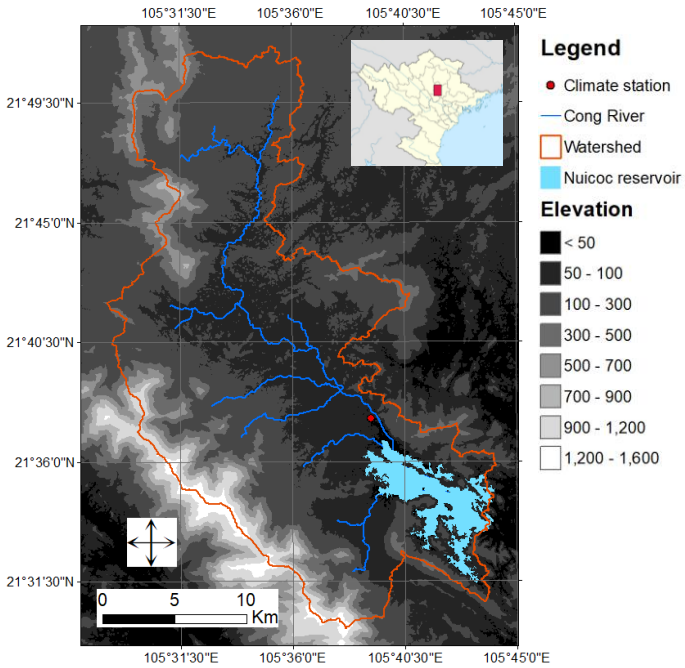


Figure 3.3. Location of the Nuicoc reservoir and watershed in the Thai Nguyen province of Vietnam

3.2.2.2. Data sources and pre-processing for the case study

Input data for SWAT were collected from different sources (Table 3.1). The Digital Elevation Model (DEM) at 30 m x 30 m resolution was extracted from The Shuttle Radar Topography Mission (SRTM) database (Earthdata Search). Land-use, land cover (LULC) maps of 2004 and 2014 were provided by the Thainguyen Department of Resources and Environment and were processed to be usable in SWAT. The soil map and soil profile

were obtained from the Food and Agriculture Organisation and the United Nations Education, Scientific, and Cultural Organisation (FAO-UNESCO) Soil Map of the World (FAO/UNESCO). The DEM, LULC map and soil map were then re-projected to suit the local conditions. For climate data, daily precipitation was collected at a local meteorological station in the watershed while other climate data including temperature, humidity, wind and solar were taken from Climate Forecast System Reanalysis (CFSR) (Saha et al., 2010). The growth phases of crops were obtained from local data (Table S13).

Table 3.1. Input data for the SWAT

Data	Duration	Source	Collection month
Digital Elevation Model (DEM) (30mx30m)		The Shuttle Radar Topography Mission database (Earthdata Search)	
Land-use	2004, 2014	Thainguyen Department of Resources and Environment, 2018	2/2018
Soil map and properties		FAO (FAO/UNESCO)	
Rainfall	2002-2013	Vietbac Centre for Hydrology and Meteorology, 2018	2/2018
Calculated inflow	2004-2013	Thainguyen Irrigation Management Company, 2018	2/2018
Other climate data	1979-2013	Climate Forecast System Reanalysis (Saha et al., 2010)	
Growth phases of crops		Handbook of plantings (*Handbook of Plants*, 2020)	

There are no gauging stations in the watershed to measure the streamflow and sediment, but there is a water level station in the reservoir. Based on monthly rainfall, evaporation, water spillage, water releases, and water levels in the reservoir, the monthly water inflows to the reservoir were calculated by using the water balance equation. We used these water inflows as measured data for model calibration and validation. For measured sediment, the Ngo Le (2010) conducted an inspection in 2001 to assess the reservoir storage after 25 years operating from 1976. The results showed that about 13 million cubic meters (Mcm) of sediment had been transported into the reservoir (Ngo Le, 2010). That means the reservoir received an average of 0.5 Mcm of sediment each year. It is assumed that sediment yield remains stable at an average rate of 0.5 Mcm each year during the calibration and validation period (2004-2013).

The Nuicoc reservoir has just one outlet and there are no sluices for flushing sediment. It is expected that during significantly high events, and the spillway is used, an amount of sediment will go downstream of the reservoir. The reservoir capacity to annual inflow is, however, approximately 0.5, resulting in a very high potential trapping efficiency (Brune,

*1953). For simplicity, this study assumed that 100% of sediment inflow was trapped in the reservoir.*3.2.2.3. Case study calibration and validation

The following steps were followed to calibrate and validate the SWAT model for the case study (Abbaspour, 2013; Winchell et al., 2013):

Step 1: The SWAT model was setup using input data summarized in Table 3.1.

The simulation period was 12 years from 2002 to 2013, in which two years were used for the warm-up period. The 2004 LULC map was used for calibration from 2004 to 2010 and the 2014 LULC map was used for validation for the next period. An initial run was conducted to compare the observed data and initial simulated data. It was necessary to analyse the initial behavior of the model to select suitable parameters for the next step using SWAT-CUP. (Abbaspour et al., 2015).

Step 2: SUFI2 in SWAT-CUP was used to calibrate the model.

Suggested rules for parameter regionalization of SWAT based on the comparison between observation and initial simulations before calibration were followed Abbaspour et al. (2015). The SUFI2 module was used. For our case study, while there was a good match for the seasonal streamflow patterns, there was less agreement for peak flows. The Curve Number (CN2), baseflow alpha factor (Alpha_bf), deep aquifer percolation fraction (Rchrg_dp), threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN), and soil available water capacity (Sol_awc) parameters for the simulations were determined as the most sensitive parameters to the peak rate of streamflow, as suggested by Abbaspour et al. (2015). These were then used to improve the calibration.

The Nash-Sutcliffe objective function for calibration was used and the threshold was set to 0.5. To quantify the fit between simulation results (95PPU) and observations expressed as a single signal, two statistics are used by SUFI2: P-factor and R-factor. The P-factor is the proportion of observed data enveloped by the simulated results (95PPU). The R-factor is the thickness of the 95PPU envelope (Abbaspour, 2013). P-factor is recommended to be over 70% for stream flows, while R-factor is around 1. However, no hard numbers exist for what these two factors should be (Abbaspour, 2013). SUFI2 took several iterations to get suitable P-factor and R-factor values to ensure proper calibration. The ranges of parameters are smaller after each iteration and produce better results than the previous iteration (Abbaspour, 2013). Each iteration needs at least 200 simulations to consider possible parameter combinations (Abbaspour et al., 2007). The final result of

the calibration process was the best range of parameters that leads to a 95PPU of outputs (streamflow and sediment).

The evapotranspiration (ET) in the watershed also plays an important role in the water balance of the model. Median potential and actual ET (PET and AET) obtained from SWAT-CUP were compared with the PET and AET generated by the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite at a resolution of 500m pixel to check the calibration.

Several related sediment parameters were adjusted in SWAT (i.e. cover and management factor (USLE_C), sediment transport coefficient (Spcon)) so that the average annual sediment yield generated over the period from 2004 to 2014, using the land-use baseline map in 2014, was equal to the average measured sedimentation (0.5 Mcm per year).

Step 3: Validation with a different range of years.

The model was validated with data from the 2011-2013 period with climate data and a 2014 land-use map. P-factor and R-factor values were calculated and analysed to judge the strength of the validation.

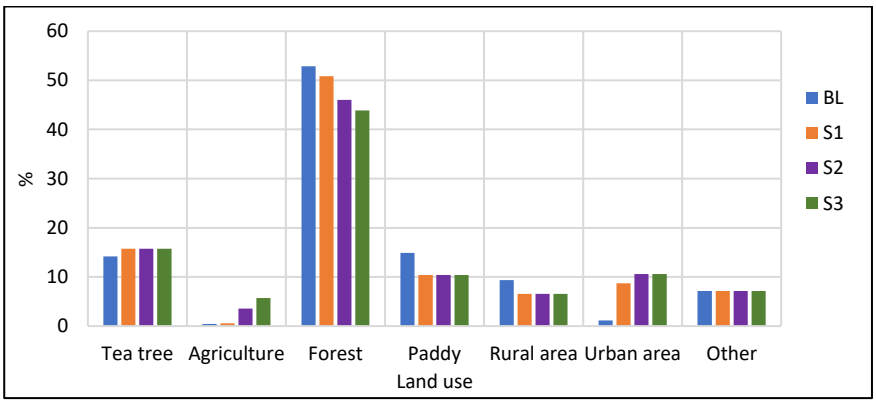
Step 4: Running SWAT-CUP using the best ranges of parameters for assessing the impact of land-use change on stream flows under the baseline map in 2014 and three possible scenarios.

3.2.2.4. Land-use change scenarios

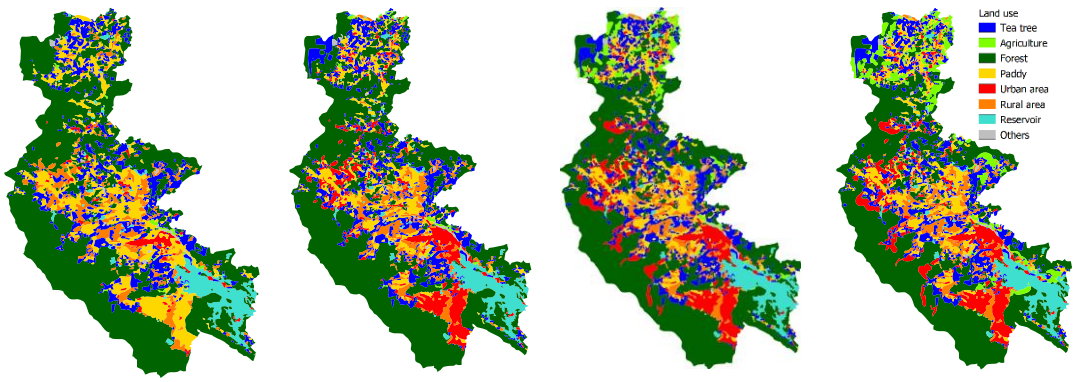
Land-use change scenarios were developed of possible future trends to allow decision-makers to plan for varying situations. Due to high socio-economic growth, the main drivers for land-use change in the reservoir's watershed are urbanisation and conversion from forest to agricultural area. The Land Change Modeler (LCM) (Eastman, 2009) was applied to project land-use transition for the case study. LCM is extensively used to simulate the projection of land-use changes between two periods based on available land-use maps (Shrestha et al., 2018). The three land-use scenarios and the land-use distribution of each scenario in this research were projected based on the land-use map in 2004 and 2014 (Figure 3.4).

- The baseline map (BL) using the land-use map in 2014.
- Scenario 1 (S1) shows a slight decrease in forest area, by 5%. The paddy and rural area decline considerably due to increase in the urban area, while the urban area will increase up to 8%.

- Scenario 2 (S2) will witness a significant reduction in the forest area, by 8% while the urban and agricultural area will rise to over 10% and 4% respectively.
- Scenario 3 (S3) is an extreme scenario with the highest urban and agricultural area and the lowest forest area.



(a)



BL S1 S2 S3

(b)

Figure 3.4. Percentage of each land-use in the Baseline and land-use change scenarios (a); BL and projected scenarios of LULC change (b)

3.2.2.5 Accounting for uncertainties in inflows and water demands

To assess the impact of land-use changes on water supply reliability under uncertainties in inflows to the reservoir and water demands during the operational period, the following uncertainties were included:

- Uncertainty in future potential land-use scenarios

  The main drivers for land-use changes are urbanisation and conversion from forest to agricultural area. The study considers three possible scenarios (S1, S2, and S3) in the watershed.
- Uncertainty of water inflows to the reservoir due to uncertainty in parameters

Monthly inflows generated by SUFI2 in SWAT-CUP within 95PPU vary based on their frequency distributions. To simplify the quantification of inflow uncertainties, we used a separate uniform distribution for each month which will produced flows completely independent of the other month. The combination of the random monthly inflows over the simulation period creates a unique inflow time series within an area bounded by the lower values and upper values of 95PPU. Different inflow time series were fed to the optimisation tool.

- Uncertainty of demands

  As this study only considers the impact of land-use changes on reservoir reliability, the climate data and water demands were kept constant. The uncertainty in monthly water demands during the operational timeframe is considered. Based on the summary of the historical data (Figure 3.5), the monthly demands from urban use, agriculture and downstream flow requirements during the operational period are assumed to follow uniform (max, min) and triangular distributions (max, median, min), respectively. The combination of the random monthly water demand generates a water demand time series for the optimisation tool.

- Uncertainty in sediment inflows

  Parameter uncertainty will in turn result in uncertainty in streamflow, which is described by the 95% prediction uncertainty (95PPU) in SWAT-CUP. This also leads to uncertainty in sediment inflows, which is also expressed as 95PPU.As higher water inflows to the reservoir will generate a greater amount of sediment, there is a close relation between water and sediment inflows. It is assumed that the relation between water inflows and sediment inflows obtained from 95PPU in SWAT-CUP is linear. The study also assumes that, at the beginning of simulation, sediment will be distributed equally on the bottom of the reservoir within the active storage since the reservoir dead storage has been full after 40-year operation, from 1982; and that, the inclusion of sediment will not affect the reservoir surface.

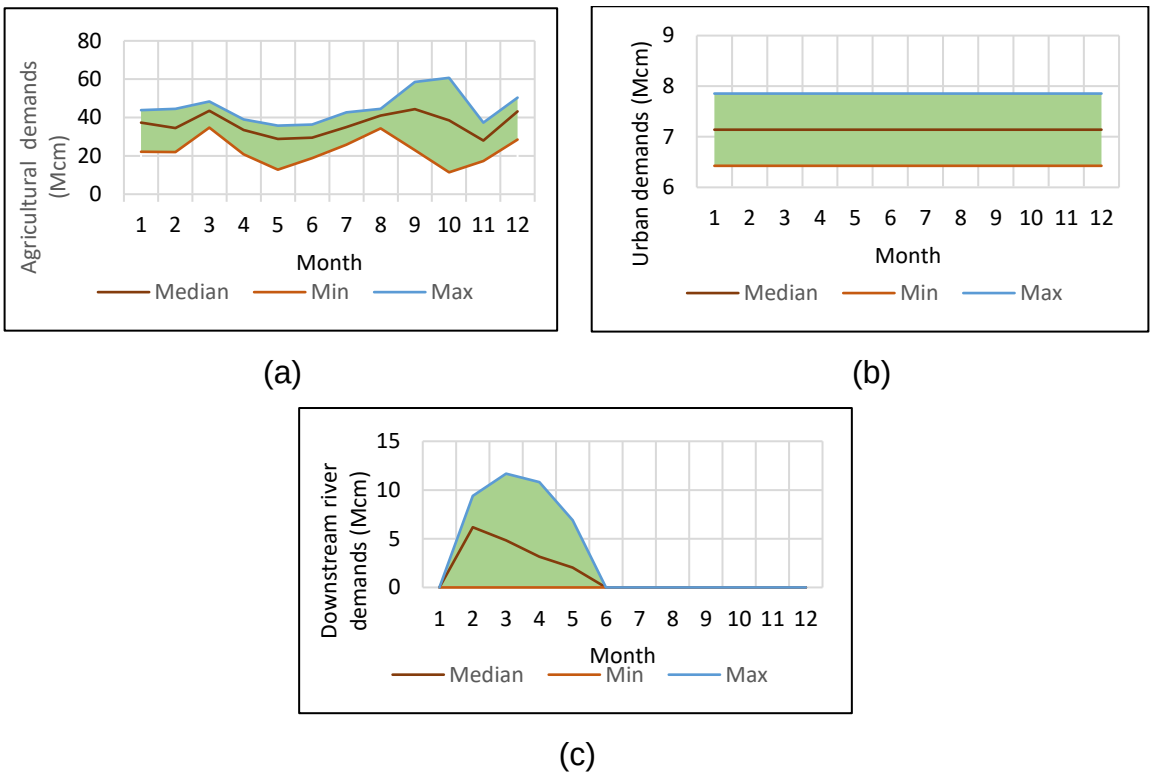


Figure 3.5. Historical water demand distributions from agriculture (a), urban use (b) and downstream river (c).

3.3. Results

3.3.1. SWAT model calibration and validation for water inflows and evapotranspiration

The SWAT model parameters were calibrated to ensure a good fit between observed and simulated water inflows as well as a good fit for evapotranspiration from MODIS and simulations. For water inflows, the P-factors indicate that 79% and 75% of observed data was within the 95PPU range in the calibration and validation, respectively (Figure 3.6, Table 3.2). This satisfied the goodness-of-fit range proposed by Abbaspour (2013). In addition, as suggested by ASABE (2017), the best simulation provided very good values of NS and PBIAS which are 0.85 and 2.37%, respectively (Table 3.2).

Table 3.2. The evaluation of SWAT model calibration and validation for water inflows.

Modelling period	land-use map	Evaluation statistics for Model Uncertainty		The best simulation		
		P-factor	R-factor	NS	PBIAS	R^2
Calibration (2004-2010)	2004	0.79	0.75	0.85	2.37%	0.86
Validation (2011-2013)	2014	0.75	0.59	0.88	-4.96%	0.88

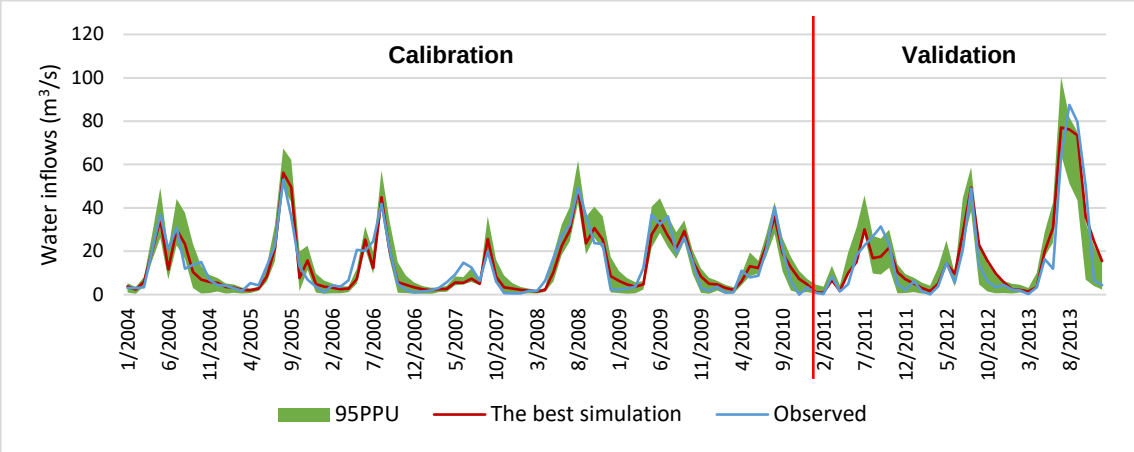
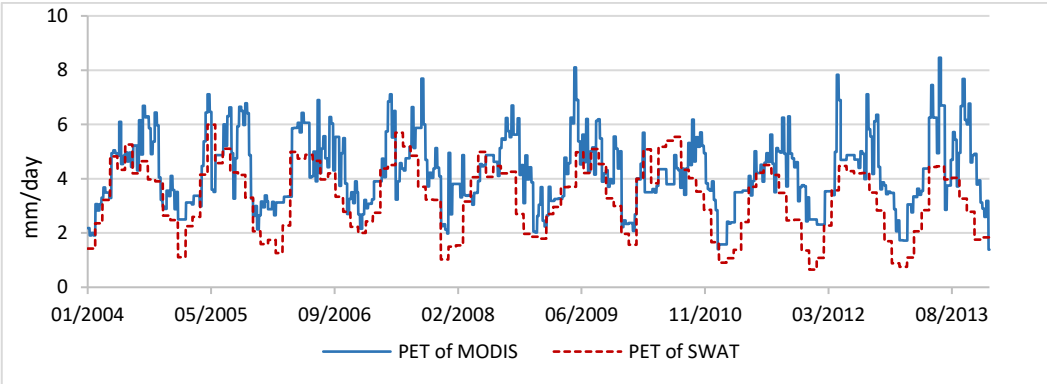
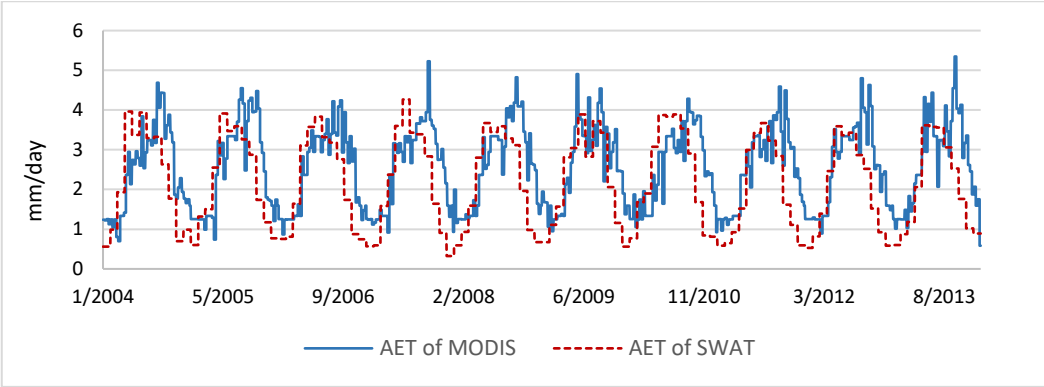


Figure 3.6. Calibration and validation of water inflows.

To ensure the calibration adequately captured land cover and crop parameters, potential evapotranspiration (PET) and actual evapotranspiration (AET) from SWAT were compared with those estimated by the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite. SWAT and MODIS use the Penman-Monteith equation to calculate PET and AET (DAAC, 2018; Neitsch et al., 2011). PET and AET were extracted from sub-basin 14 and compared with those of MODIS in the same region. It was observed that SWAT PET/AET and MODIS's overall seasonal dynamics are similar (Figure 3.7). The average daily PET value from SWAT is 3.3 mm/day, while that of MODIS is higher at about 4.25 mm/day. The AET of SWAT (2.45 mm/day) and MODIS (2.17 mm/day) are closer.



a) PET of SWAT and MODIS.



b) AET of SWAT and MODIS.

Figure 3.7. Comparisons of PET (a) and AET (b) determined with the calibrated SWAT model and MODIS.

There is no sediment time series data for an extended calibration or validation of sediment inflows; however, the 95PPU of sediment inflows closely follows the water inflow pattern. The annual average of simulated sediment inflows to the reservoir is approximated at a median of 0.516 Mcm/year (Figure 3.8), equal to historical average measurements for the period from 1976 to 2001 (0.5 Mcm/year) (Le Ngo, 2010).

3.3.2. SWAT model output

The calibrated parameter ranges were applied in the SWAT-CUP model to run simulations for the baseline (BL) land-use and each scenario (S1, S2, and S3). S1, S2, and S3 generate 2.5%, 3.7% and 4.1% higher average water inflows than BL, respectively (Table 3.3). While S3 has the highest average water inflows (16.12 m^3/s), especially in wet seasons (27.3 m^3/s), followed by S2 (16.07 m^3/s), their dry water inflows are the lowest, at 4.93 m^3/s and 4.95 m^3/s, respectively. The expected 10-year sediment inflows under S3 were the highest (11.54 Mcm), because this scenario has the largest transition from forest areas to the agricultural areas, and the change occurs near the reservoir (Figure 3.9). In contrast, the baseline and S1, with the largest forest area and the lowest agricultural areas, produces the lowest sediment inflows into the reservoir (approximately 5 Mcm) (Table 3.3, Figure 3.8).

Table 3.3. Water inflows to the reservoir over a 10-year simulation (extracted from the median of 95PPU).

Scenarios	Water inflows (m^3/s)	Sediment inflows (Mcm/10 year)	Water inflows in wet seasons (m^3/s)	Water inflows in dry seasons (m^3/s)
BL	15.49	5.16	25.998	4.973
S1	15.88	5.02	26.799	4.966
S2	16.07	5.83	27.196	4.949
S3	16.12	11.54	27.304	4.928

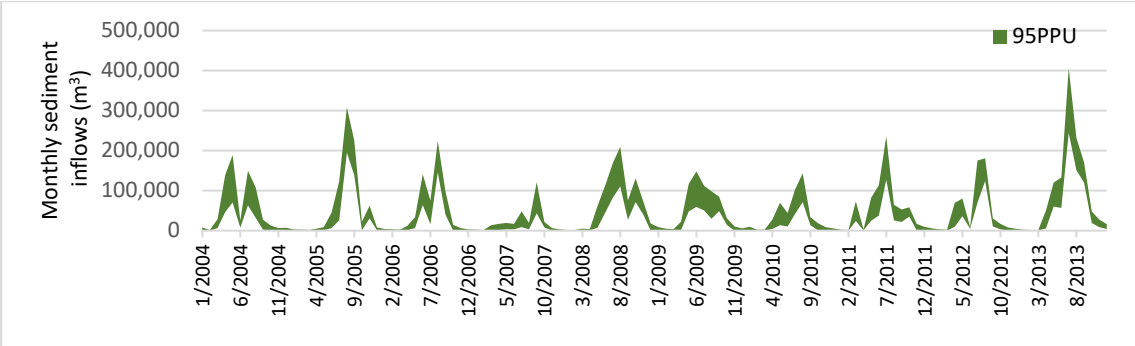
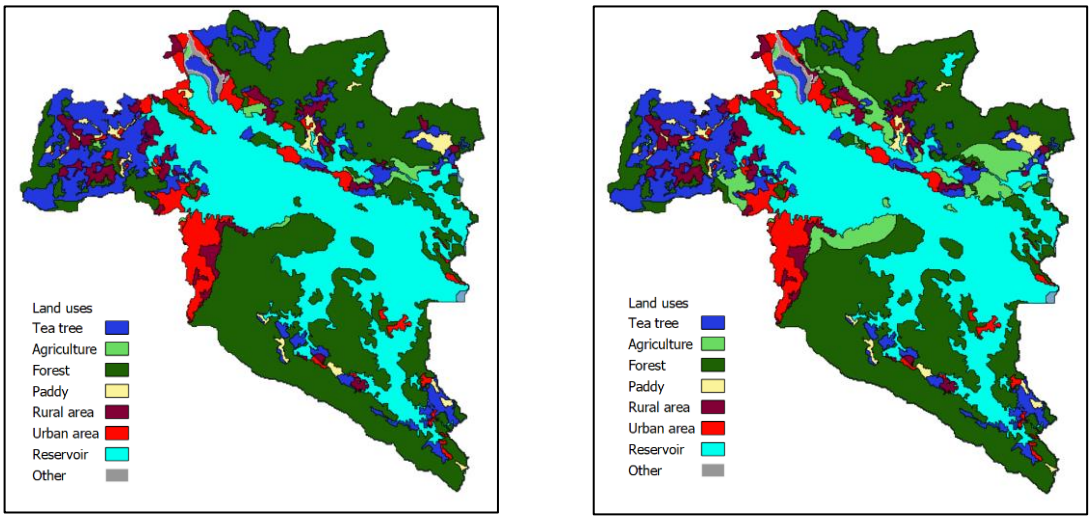


Figure 3.8. Sediment inflows into the reservoir using the baseline land-use map.



(a) (b)

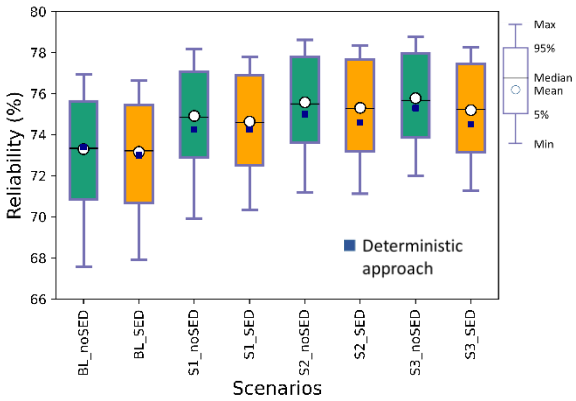
Figure 3.9. Transition from forest to agricultural areas surrounding the reservoir, under S2 (a) and S3 (b).

3.3.3. The impact of land-use changes on performance indicators of the reservoir

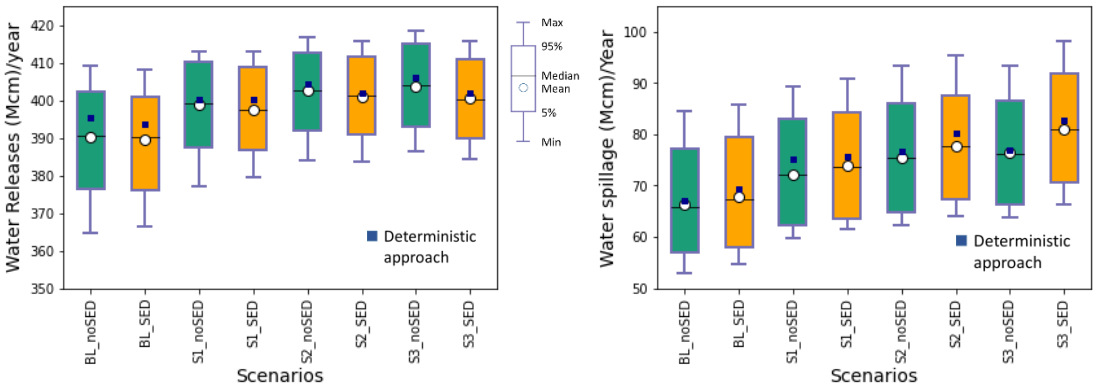
Probabilistic and deterministic simulations were conducted to quantify the impact of land-use change on water supply reliability under BL, S1, S2 and S3. The impact of land-use changes without including reservoir sedimentation was compared to simulations including reservoir sedimentation over a period of 10 and 40 years, because it was hypothesised that changes in sedimentation could significantly affect the reservoir's storage over a relatively long time period. Differences in reservoir performance indicators were quantified between scenarios and between the 10-year period and 40-year simulation periods (Figure 3.10).

Independent sample t-tests were conducted to compare performance indicators of the baseline with those of each scenario simulated using the probabilistic approach (Table S2-S12). In general, there was a significant difference in reservoir indicators between the baseline and each of the scenarios. Under the same climate and water demands, the growth in the urban areas and conversion from forest to agricultural areas will increase

water releases, water spillage, and reliability of the reservoir when sedimentation was not considered (Figure 3.10-a, b, c). For the baseline, while the agricultural and urban areas make up the lowest percentage, at 0.5% and 1% respectively, the forest areas account for the highest percentage, about 52%. The median of water releases is projected to be 39.0 Mcm/year. There will be a 90% chance the reliability will be from 71% to 76%. Water spillage generated by the baseline are the lowest, with a median of 65 Mcm/year. The land-use change from BL to S3 results in a decline in the forest areas from 52% to 44%, and significant growth in the urban areas and agriculture areas from 2% and 1% to 11% and 6%, respectively. This will produce the highest surface-runoff as well as water inflows to the reservoir. There is a 90% chance that the water releases will range from 392 to 415 Mcm/year and the reliability will vary from 74% to 78%. However, the water spillage in wet seasons due to excessive water caused by S3 are the largest, with a median of about 75 Mcm/year. S2 is projected to have the same land-use areas as S3, except for 2% higher forest areas and 2% lower agricultural areas. The t-tests show that there was an insignificant difference in reliability between S2 (M=75.6%, SD=1.3%) and S3 (M=75.8%, SD=1.3%); t(358) = -1.449, p = 0.148 (Table S2). Although S1 is projected to have just a 2% lower forest area than the baseline, the considerable increase in the urban areas seems to increase water inflows to the reservoir. There was a significant difference in reliability between the baseline land-use (M=73.30%, SD=1.56%) and S1 (M=74.9%, SD=1.3%, t (358)= -10.57, p = 0.00 (Table S2). This will increase the reliability and water releases by 1.5% and by a median 9 Mcm/year, respectively.



(a)



(b) (c)

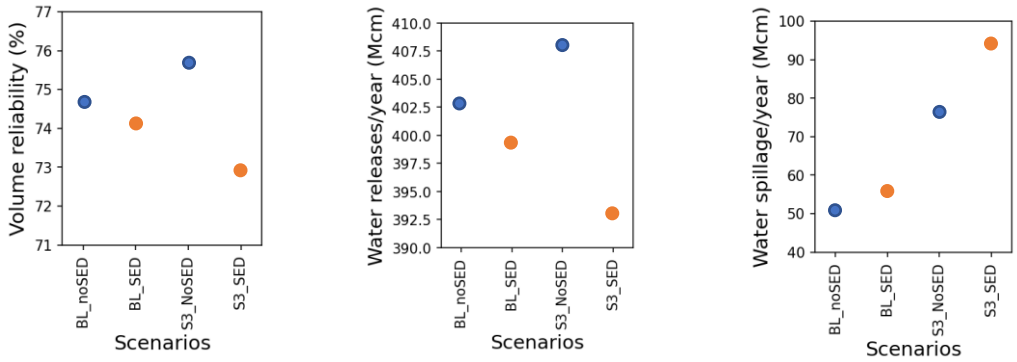
Figure 3.10. Impact of land-use changes on the reservoir's operation using the probabilistic and deterministic approaches for the 10-year period. (the suffix:_NoSED: Sedimentation not considered; _SED: Sedimentation considered)

When sedimentation was considered over a 10-year period (Figure 3.10), there are small decreases in performance indicators, except for water spillage. Statistical t-tests showed that while water supply reliability generated by S3 (M=75.2%, SD=1.3%) is insignificantly different from that of S2 (M=75.3%, SD=1.3) t(358) = 0.809, p=0.419 (Table S3), S3's indicators are significantly different from those in S1 (M=74.6%, SD=1.3%); t(358) = -4.07, p = 0.00 (Table S3), and the baseline land-use (M=73.2%, SD=1.5%), t(358) = -13.8, p = 0.00 (Table S3). Sedimentation will make water releases in S3 decrease from 405 to 400 Mcm/year. In contrast, sedimentation causes greater water spillage in the wet seasons. Compared with the case where sedimentation was not included, the water spillage of the baseline will increase by 2 Mcm/year in the median while that of S3 will increase by 5 Mcm/year.

The deterministic approach was run within the same timeframe as the probabilistic approach (Figure 3.10). The trend in the median of the performance indicators for the probabilistic approach is similar to that of the indicators determined with the deterministic approach. The difference was found to be less than 5%.

Although sediment yield has an impact on the reservoir's operation, this impact is insignificant in the 10-year simulation timeframe. Therefore, to investigate the performance over an extended period, a 40 year simulation using the deterministic approach was conducted using the baseline and S3 (Figure 3.11). The climate data and water demands over the 40 years were extended from the 10-year baseline data. Results showed that, when the sedimentation was included the reliability and water releases under S3 decreased by 3% and 15 Mcm/year, while those under BL declined by

approximately 0.6% and 4 Mcm, respectively (Figure 3.11-a, b). The increase in water spillage under S3 (17 Mcm/year) is significantly greater than the increase of 5 Mcm/year under BL between with and without reservoir sedimentation (Figure 3.11-c). Compared with 10-year simulations, the sedimentation over 40-year simulations will make the reliability and water releases under S3 decrease by 2% and 8 Mcm/year, respectively. It will also cause more risk of downstream flooding by increasing water spillage by 15 Mcm/year.



(a) (b) (c)

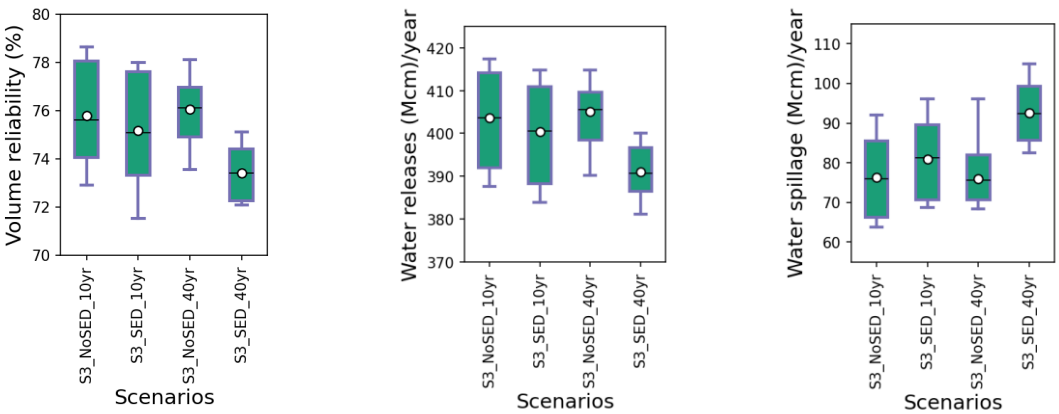
Figure 3.11. Assessing the reservoir operation under uncertainties over 40 years using deterministic approach (the suffix:_NoSED: Sedimentation was not considered; _SED: Sedimentation was included)

An analysis of the impact of optimisation iterations and simulation run times was also conducted for the probabilistic approach. A range of water supply reliabilities, under S3 without ongoing reservoir sedimentation, were tested with different numbers of combinations (n) of water, sediment inflows and water demands (Figure 3.12, Table 3.4). The n-value of 500 produced the range of reliability of 7.3%, from 72.1% to 79.4%, which was much wider than the n-value of 50 and 100 with 4.9% and 5.7%, respectively. The reliability range generated by the n-value of 500 was slightly broader than the n-value of 180 and 300 (approximately 6.8%). However, simulations with the n-value of 500 took the longest time to run, around 141 hours. Although the reliability range of n-value of 100 was 1.6% lower than that of n-value of 500, the former is computationally more efficient for long term studies as it took less 113 hours than the latter, and the median and mean reliabilities achieved by these two these n-values are the same (Table 3.4).

Table 3.4: Difference in the range of water supply reliability over 10-year timeframe generated by the number of combinations of water, sediment inflows and water demands (n)

n-value	Range of reliability (%)	Median reliability (%)	Mean reliability (%)	Computational cost (hours)
50	73.7-78.6	75.7	75.7	14
100	72.9-78.6	75.6	75.8	28
180	72.0-78.8	75.7	75.8	51
300	72.1-78.9	75.7	75.8	85
500	72.1-79.4	75.8	75.7	141

Based on the probabilistic approach using an n-value of 100, the reservoir indicators were calculated under S3 with and without sedimentation over 10 years and 40 years (Figure 3.12). The t-test showed that the reliability with sedimentation over 40 years (M=73.4%, SD=0.6%) was significantly different from that over 10 years (M=75.8%, SD=1.2%); t(198) = 17.23, p = 0.00) (Table S12), but their median values have the same trend as found for the deterministic approach.



(a) (b) (c)

Figure 3.12. Water supply reliability under uncertainty over 10 and 40 years using the probabilistic approach with an n-value of 100 (the suffix: _NoSED: Sedimentation was not considered; _SED: Sedimentation was included; _10yr: 10-year simulation; _40yr: 40-year simulation)

3.4. Discussion

3.4.1. The modelling framework

The framework allows for both deterministic and probabilistic optimisation studies. The deterministic approach provides the overall trend of changes, but it does not capture the uncertainties in water inflows, sediment inflows and water demands over the operational timeframe. In contrast, the probabilistic approach not only provides the trend of changes, but also describes the range of possible outputs based on a wide range of possible combinations of input data. The probabilistic approach can, thus, provide the probability

that the performance indicators will be greater or lower than specific values, thereby supplying decision-makers with more valuable information, as also pointed out in previous research (Al-Harthy, 2010). Nevertheless, the probabilistic approach as applied in this framework seems to have several limitations. Firstly, this approach comes at a higher computational cost than the deterministic approach, because the probabilistic approach considers hundreds of possible input combinations compared with only one possible combination considered by the deterministic one. Secondly, as the distributions of monthly inflows between the lower and upper bound of 95PPU were demanding to obtain, the probabilistic approach uses uniform distributions to quantify uncertainty in monthly water inflows to form the time series within 95PPU, and assumes a linear relationship between water inflows and sediment inflows. In addition, the selection of the number of possible combinations (n) of inflows and water demands is a factor which impacts on the effectiveness of the probabilistic approach. A greater n-value will lead to a wider range of water supply reliability, since the Latin Hypercube algorithm will use greater n-values to help consider more feasible combinations over the operational timeframe (Goodarzi, 2013; Thomopoulos, 2012). The n-value of 180 used in this study was acceptable for the balance between the range of reliability and computational cost, and ensured the accuracy of the model (Table 3.4). Lastly, it is also noted that the range of reliability over 40 years was narrower than that over 10 years (Figure 3.12). This may be due to the number of months, n-value or sedimentation considered for the two timeframes.

Another improvement of the framework could be to use the actual time series of water and sediment inflows directly generated through simulations via SWAT-CUP (Abbaspour, 2013). In this case, a uniform distribution of water inflows would not have to be assumed, nor a linear relationship between water inflows and sediment inflows. The n-value would not have to be chosen either. However, this approach would require a more complex program interference between SWAT-CUP and the optimisation tool.

The effects of water quality and best management practices (BMP's) for erosion and nutrient reduction were not considered in the framework. Through BPM's the water quality could be controlled to reduce reservoir sedimentation and water quality issues.

3.4.2. Impact of the change in urban areas and conversion from forest to agricultural areas on performance indicators

The application of the framework for the Nuicoc reservoir indicated that the changes in urban areas and transition from forest to agricultural areas through land-use scenarios

(Figure 3.4) could affect the multipurpose reservoir's performance indicators. The level of impact of land-use on water and sediment changes is similar to those found in other research (Shrestha et al., 2018; Zhang et al., 2019), but the framework further allows for quantifying performance indicators for multi-purpose reservoirs to determine impacts on water supply. Apart from attenuating the reservoir storage and water releases, land-use increasing sediment will result in more excessive water spillage in wet seasons and pose a serious risk of flooding events in downstream areas (Mescher; Munthali et al., 2011).

This study used the deterministic approach to compare the water spillage from the reservoir between the baseline and S3 (Figure S1). When sedimentation was not included, S3 generates more water spillage in the wet seasons (i.e. July, August, September, October). When sedimentation was included under S3, there are higher peak values as well as duration in the water spillage. Therefore, greater water and sediment inflows, as the result of land-use changes, will affect not only the water supply reliability, but also affect downstream flood risk.

3.4.3. Impact of spatial distribution of land-uses

Although there is a small change (2%) in the forest and agricultural areas between S2 and S3, the total sediment inflows to the reservoir under S3 (11.54 Mcm) is much greater than S2 (5.83 Mcm) (Table 3.3 and Figure 3.4). Although S2, has approximately 5% lower forest areas and 3.5% higher agricultural areas than those under S1 and the baseline, the sediment inflows generated by S2 are slightly higher than S1 and the baseline. We found that many agricultural areas under S3 are converted from forest areas near the reservoir. Although many agricultural areas under S2 and S3 are concentrated in the north of the watershed, most sediment yield generated by these areas will be deposited along the main streams (Figure S2). The main reason is that the sediment yield in the sub-basin containing the reservoir is approximated at 102 ton/ha/year under S3, while that under S2 is much lower, around 22.5 ton/ha/year, as the agricultural areas under S3 (479 ha) are roughly five times that of S2 (88 ha). As a result, S3 will generate the highest sediment deposition in the reservoir. Thus, the importance of land-use distribution, which has been mentioned in other research for the same region (Le Ngo et al., 2007) or other regions (Ausseil et al., 2008), should be emphasised in the planning and managing of land-use.

3.5. Conclusions

The impact of possible land-use changes on the reliability of reservoir water supply was investigated through the development of a framework which couples the @RISK optimisation tool and SWAT. The probabilistic optimisation approach was shown to provide significant benefits over the deterministic approach in determining the possible range of reliabilities under uncertainties in water and sediment inflows, and water demands, providing decision-makers with more information in the context of future uncertainty; however, this comes at a cost of computational demand.

The application of the framework to the Nuicoc multi-purpose reservoir located in Thainguyen, Vietnam for determining water supply reliability demonstrated the need to accurately estimate erosion and sedimentation as it has a major long-term influence on water reliability because sediment accumulation in the reservoir will attenuate the storage capacity and diminish water supply. In addition, expanding urban areas and conversion from the forest areas to agriculture will generate more water inflows as well as a greater variation in the range of the reservoir's reliability.

This study did not consider climate change, as the focus was on understanding the impact of land-use changes on reservoir operations. Future studies, however, should include a broader range of uncertainties, such as combined climate change, land-use change and water demands, to project the water supply reliability of reservoirs. Knowledge of the effects of a broader set of uncertainties will help decision makers to be better prepared and formulate adequate policies for the management of water resources, land-uses and sedimentation.

Chapter 4 . UNCERTAINTY OF LAND USE AND CLIMATE CHANGE ON RELIABILITY, RESILIENCE AND VULNERABILITY IN RESERVOIR WATER SUPPLY

4.1. Introduction

Water supply from multi-purpose reservoirs is influenced by many factors including population growth, climate change, land use change and water resources management (Abera et al., 2018; Shrestha et al., 2018; Ziaei et al., 2012). Human induced land use changes within watershed-reservoir system can alter the streamflow and transport of sediment into reservoirs (Shrestha et al., 2018; Zhang et al., 2019), and thus impact their water supply reliability, resilience and vulnerability (RRV). Furthermore, climate change also influences reservoir operations (Lee et al., 2016; Zhang et al., 2014) and water availability of reservoirs (Shrestha et al., 2016) through alterations in precipitation, temperature, and solar radiation (Farinosi et al., 2019; Liu et al., 2020). Land use and climate change are, therefore, identified as the main factors impacting the hydrological process and sediment yield of a reservoir watershed (Farinosi et al., 2019; Tamm et al., 2018). While a reservoir plays a crucial role in supplying water for multiple purposes such as downstream agriculture, recreation and urbanisation, growing demands from those individual sectors lead to a variety of constraints that need to be addressed (Goodarzi et al., 2013). It is thus important to estimate the RRV of a reservoir water supply based on optimisation analyses under uncertainty in future land use and climate change and suggest options to improve the reliability of reservoir.

Many studies have considered the impact of climate change and/or land use change on hydrological conditions within river watersheds in different geographic areas (Chen et al., 2020; Khoi et al., 2014; Liu et al., 2020; Shrestha et al., 2016). As most studies point out, the conversion from forest to cultivation area would generate more run-off and sediment, and increasing urban areas can also result in greater run-off (Choto et al., 2019; Shrestha et al., 2018; Zhang et al., 2019). In addition, many researchers have also indicated the significant effect of climate change on reservoir inflows under various Global Climate Models (GCMs) and Representative Concentration Pathways (RCPs) (Muhammad et al., 2020; Shrestha et al., 2016). A variety of studies also demonstrate that coupled climate and land use changes also cause greater impact on stream flows and sediment yield within a watershed than each of those individually. In the Be river watershed, Vietnam, the annual streamflow and sediment load under the combined effect of climate and land

use change increased by 28% and 46%, respectively, compared to 1.2% and 11.3% caused by only land use change, and 26.3% and 31.7% caused by just climate change, respectively (Khoi et al., 2014). However, there appears to be no studies investigating the impact of varying hydrological processes on the reliability, resilience, and vulnerability of reservoir water supply under combined future climate and land use changes.

The RRV criteria to assess reservoir performance was originally suggested by Hashimoto et al. (1982). The reliability describes the probability that the system is in a satisfactory state, but this indicator does not show how quickly reservoir water supply recovers and returns to a satisfactory value. According to Loucks et al. (2017), “a reservoir, which may fail quite regularly but by insignificant amounts and for short durations, will be preferred to one whose reliability is much higher, but when failure happens, it can be considerably more severe”. Resilience and vulnerability supplement the more common reliability indicator and thereby provide a more complete picture of risk in reservoir performance (Moy et al., 1986). These important criteria assist in the evaluation and selection of operating policies for water resources projects. Nevertheless, while RRV have been considered based on optimisation analyses by many studies (i.e. i.e. Ehteram et al., 2018; Hashimoto et al., 1982; Jain et al., 2008; Kjeldsen et al., 2004; Moy et al., 1986), these reservoir indicators have not been estimated in the context of combined future land use and climate change.

There are numerous hydrological tools available to consider the impact of land use and climate (Dwarakish et al., 2015). The framework using the combination of Soil and Water Assessment Tool (SWAT) and @RISK genetic algorithm optimisation tool was demonstrated to be useful in investigating the RRV of a reservoir under uncertainty in land use change (Chapter 3). This approach used a probabilistic optimisation approach, considering uncertain factors such as water inflows and sediment inflows due to model parameters, to provide the possible range of RRV. In most situations, the probabilistic approach can actively support decision-makers with greater information and visualisation (Al-Harthy, 2010). To determine the reliability of reservoir in future, climate change should be also considered in that framework as future climate will significantly vary and affect reservoir operation.

Vietnam is one of the world’s most vulnerable countries to the effects of climate change (MONRE, 2016; USAID, 2021). Increasing temperatures, sea level rise, worsening droughts and floods, and increased frequency of storms are the key factors that threaten lives, food security, and livelihoods of millions of Vietnamese. Furthermore, the socio-

economic development in this rapid developing nation has led to noticeable change in land use in recent decades (Khoi et al., 2014). The Nuicoc watershed-reservoir system in the north of Vietnam is of particular interests as a case study because (1) the reservoir watershed is witnessing a rise in annual average temperatures, increased frequency of floods in wet seasons followed by an increase in severe soil erosion, and decreased water inflows in dry seasons (TNDRE, 2013); (2) urbanisation and transition from forest to agricultural within the watershed is quickly happening; (3) the Nuicoc reservoir is playing a crucial role in supplying water for downstream urban areas, agriculture and river flows, and in keeping high water levels in the reservoir for tourism in May; and finally (4) rising water demands are placing strain on the reservoir.

The overall aim of this study was to assess the influence of combined future land use and climate change on the RRV of a multipurpose water supply reservoir. The specific objectives were: (a) to assess the impact of combined land use and climate change on the water and sediment inflows into the Nuicoc reservoir, (b) to use a probabilistic optimisation approach to project the range of RRV of the reservoir under possible scenarios.

4.2. Material and Method

4.2.1. Study Area

The Nuicoc reservoir, situated in Thai Nguyen province, in the north of Vietnam, has the storage capacity of 175 Million cubic meters (Mcm), with a water surface area of approximately 2,500 ha. It was established to provide water for downstream urban supply, irrigated agriculture, tourism, and to sustain necessary flows for a nearby river. The annual rainfall, evaporation, and average temperature in the 575-km^2 watershed where the reservoir is located in, are approximately 1850 mm, 1100 mm and 25oC, respectively. The wet season, which often lasts from June to October, accounts for up to 75% of annual rainfall. The 60 km Cong River in the watershed contributes roughly 500 Mcm of annual inflow to the reservoir. Economic development within the watershed is happening dynamically. The transition from forest to agricultural area and urbanisation are the main drivers for land use change in the reservoir's watershed where forests account for the highest percentage, at 52% (Figure 4.1).

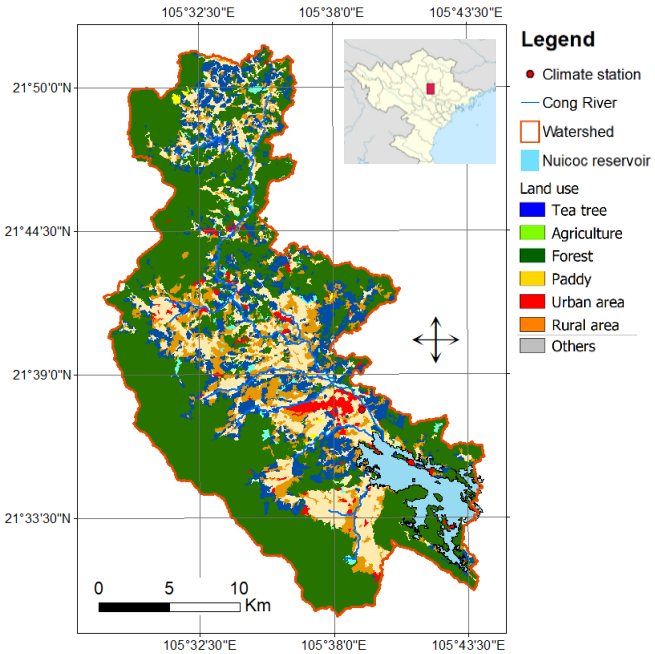


Figure 4.1. Location and land use of the Nuicoc reservoir watershed in the Thai Nguyen province of Vietnam.

4.2.2. Model setup

This study applied the optimisation framework developed in Chapter 3 to assess the RRV of the reservoir under uncertainty of combined land use and climate change (Figure 4.2). The framework couples SWAT (Neitsch et al., 2011) and the @RISK genetic optimisation tool (Palisade, 2016) and uses a probabilistic optimisation approach to provide a range of RRV in reservoir water supply. The study used two GCMs and two RCPs (4.5 and 8.5) to project the future climate for the SWAT model, which was previously calibrated in Chapter 3. Two land use change scenarios within the watershed were also simulated with the SWAT tool to generate the water and sediment inflows to the reservoir. Water demand scenarios and water allocation policies were also considered. In this study, uncertainties in future trends were quantified by water demand, land use and climate change scenarios, and uncertainties during operational timeframes of water inflow, sediment inflow and water demands were quantified by probability distributions (Chapter 3).

A genetic algorithm optimisation tool was used to minimise the sum of squared deviation between demands and water releases from the reservoir. Constraints included water balance continuity, the change of reservoir storage within maximum and minimum values, minimum water level for recreation and minimum demand priorities. The Latin Hypercube sampling method was used to generate possible combinations of water inflows, sediment inflows, and water demands as input for the optimisation model. This subsequently created a range of reservoir RRV (Chapter 3).

The Nuicoc reservoir, which has just one outlet, has no functionality for flushing sediment. The ratio between reservoir capacity and average annual inflow was calculated to be 0.5. This meant that the potential trapping efficiency was really high (Brune, 1953) and thus it was assumed that all incoming sediment was trapped in the reservoir, as discussed in Chapter 3.

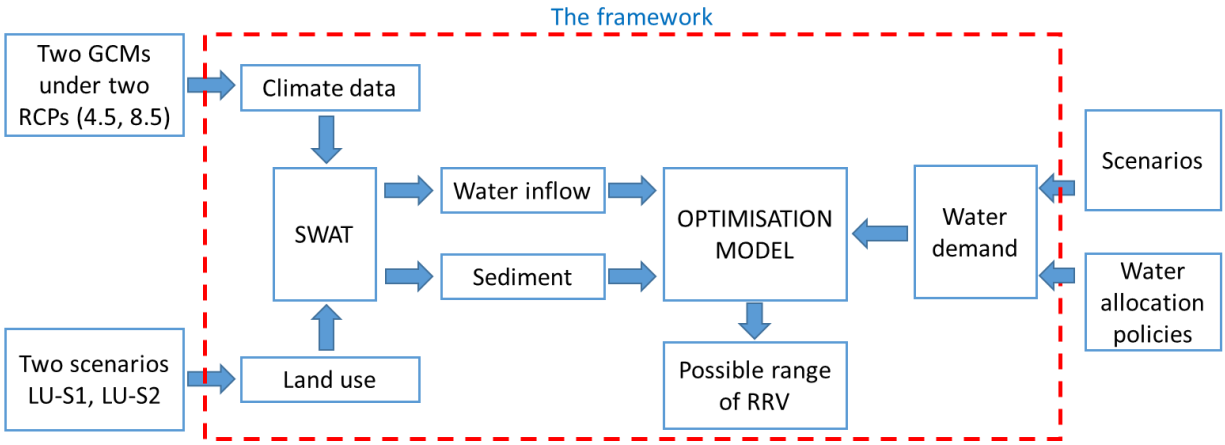


Figure 4.2. Model established for determining the possible range of RRV.

4.2.2.1. Accounting for Uncertainties

A range of uncertainties were considered in this study (Table 4.1). The uncertainties in land use and climate change were expressed by scenarios. During the 10-year operational period of the reservoir, monthly water demands vary randomly based on the historical data, and this variation was quantified by probability distributions based on monthly measured data (Table S14, Appendix B). Uncertainties in SWAT parameters also resulted in a potential range of monthly water and sediment inflows. The cumulative distributions of simulations were subsequently computed for each month of the simulation period in SWAT-CUP (SWAT Calibration and Uncertainty Programs) (Abbaspour et al., 2007). The possible range of monthly water and sediment inflows was presented by the 95PPU factor, which represents the range between the lower 2.5% and upper 97.5% (L95PPU and U95PPU respectively) of the cumulative distributions, as explained in Chapter 3.

Table 4.1. Uncertainties considered in the case study.

No.	Uncertainty	Sources	Expression of uncertainty
1	Land use changes	Based on main drivers which are urbanisation and the conversion from forest to agricultural areas.	02 Scenarios
2	Climate change	Based on the GCMs and RCPs previously applied in the same region.	02 Scenarios
3	Inflows	95PPU from SWAT-CUP.	Using uniform distribution to generate random inflow for each month between L95PPU and U95PPU.
4	Sediment	95PPU from SWAT-CUP.	Based on the relation between water and sediment inflows within Lower bound of 95PPU and Upper bound of 95PPU (Chapter 3).
5	Water demands	Based on measured data and future use.	Using Scenario and probabilistic distributions generated from monthly measured data.
	Irrigation for agricultural areas		Triangle distribution
	Downstream river		Triangle distribution
	Urban use		Uniform distribution

4.2.2.2. Climate model

The Simulator of Climate Change Risks and Adaptation Initiatives (SimCLIM) developed by CLIM systems is an integrated assessment model for studying the impacts and adaptation strategies to climate change (Warrick et al., 2012). SimCLIM mainly relies on the IPCC CMIP5 dataset and has been used to project future climate for various sectors in many different locations around the world (Amin et al., 2018; Bao et al., 2015; Kenny et al., 2000; MCR, 2018; Ramachandran et al., 2017; Warrick et al., 2005; Warrick et al., 2001; Zheng et al., 2020). Pattern scaling and bilinear interpolation was employed by SimCLIM to downscale the outputs of 40 GCMs to site-specific scales with the highest resolution being of 1 x 1 km. The climate projections were generated from 1996 to 2100 (Yin et al., 2013).

SimCLIM can only provide monthly climate data while the SWAT model requires daily climate data as inputs. A change factor between projected and baseline (1986–2005) climate data was used to modify reference daily historical data and project daily data for the 2100 timeframe. The CCSM4 and GFDL-CM3 GCMs were chosen for simulations because these models were demonstrated to be suitable to simulate climate processes in Vietnam (MONRE, 2016). In addition, they represent two wide ranges of climate projections. Compared with the baseline, the first one provides much more rainfall in wet seasons, but less rainfall in dry seasons. The other one generates more rainfall in both seasons. The climate variables considered were precipitation, temperature, and solar radiation as these factors were expected to have significant impact on streamflow, sediment yield and potential evapotranspiration (PET).

RCP2.6, RCP4.5, RCP6.0, and RCP8.5 are greenhouse gas concentration trajectories with the values of 2.6, 4.5, 6.0, and 8.5 W/m^2, respectively. They were adopted by the IPCC in its Fifth Assessment Report (AR5) for future projections up to the year 2100 (Yin et al., 2013). RCP2.6 is the scenario that has the lowest emission as RCP2.6 assumes to have the full participation of all nations in the short run to decline all the main emissions, although this is probably unfeasible in reality (Abera et al., 2018). Intermediate scenarios are represented by RCP4.5 and RCP6.0, which are slightly more energy intensive than RCP2.6. The RCP4.5 relies less on fossil fuels, using cleaner energy sources, whereas fossil fuel use is prevalent under RCP6.0 (Liddicoat et al., 2013). The RCP8.5 is a scenario lacking any mitigation action before 2100. High population growth and a low rate of technological development are assumed. Under the RCP8.5, fossil fuels will be the primary energy source, with the highest emissions of CO_2 (Liddicoat et al., 2013). The RCP4.5 (Medium emission) and RCP8.5 (High emissions) were selected in this study, as suggested by (MONRE, 2016) to represent a realistic scenario and a very conservative scenario.

4.2.2.3. Land use change scenarios

In this research, in addition to the baseline, two land use scenarios in 2100 (Chapter 3) were used (Figure 4.3).

- The baseline map (LU-BL) uses the land use map of 2014.
- Land use scenario 1 (LU-S1) will witness an 8% reduction in the forest area while the urban and agricultural area will rise to over 10% and 4% respectively.
- Land use scenario 2 (LU-S2) is an extreme scenario with the lowest forest area (at 44%), and the highest conversion from forest to agricultural areas near the reservoir (around 479 ha compared to 88 ha for LU-S1) (Figure 4.3).

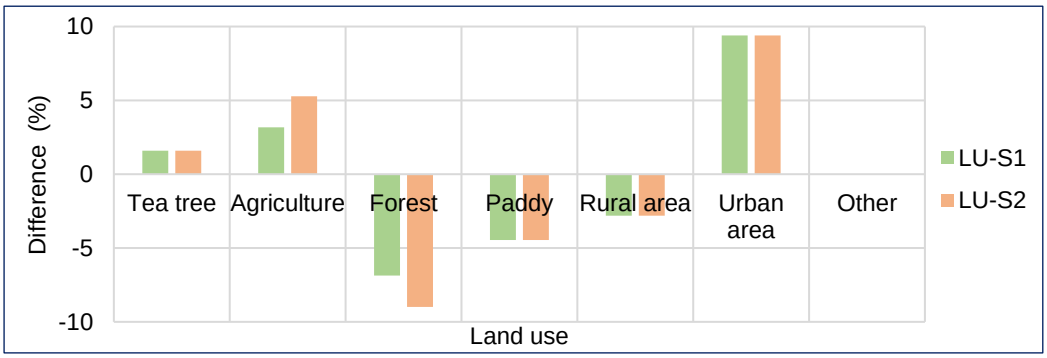


Figure 4.3. Percent difference in land use between the Baseline map in 2014 and the LU-S1 and LU-S2 scenarios.

4.2.2.4. Water allocation options

Water allocation options are defined as combinations of water demand scenarios, water allocation policies. Water demand scenarios express the change in future water use of each sector. Water allocation policies include a minimum water level for tourism and sector priority coefficients required by the government. A variety of priority coefficients for downstream agriculture and river water supply were considered, which range from 0 to 100% supply priority. If the reservoir water supply cannot meet all water demands over the operation period, particularly in dry seasons, the constraint for meeting minimum sector demand priorities was imposed (as proposed by Goodarzi et al. (2013); Ziaei et al. (2012)). The minimum allowable releases were implemented in the following equation, described in Chapter 3:

$$U_{i,j} + aA_{i,j} + bD_{i,j} \leq R_{i,j} \leq U_{i,j} + A_{i,j} + D_{i,j} \quad (4.1)$$

Where $R_{i,j}$ are water releases in month j and year i, $U_{i,j}$ are urban demands, $A_{i,j}$ are agricultural demands, $D_{i,j}$ are downstream river demands, a and b are priority coefficient for agriculture and downstream river, respectively.

The a and b values are determined based on the government policy guided by the projected economic growth within the watershed. In the case study, agricultural and river downstream demands will be sacrificed during water shortage to ensure urban water supply is met. Long term water shortages for agriculture will be dealt with by finding other replaceable water sources, changing current crops, or applying water saving irrigation methods.

Water allocation options (Table 4.2) are expressed as follows:

- The baseline: Historical water demand was used for each sector. Minimum demand priorities were applied, with priority coefficients for downstream agriculture and river set at 50% and 0% (Priority 1), respectively. BMPs were not applied. The reservoir was kept to the minimum water level at 55 Mcm in May for recreational purpose to comply with current government policy. The simulation will stop if the reservoir cannot satisfy the recreational requirement.
- Option BL0: This option simulates combined land use and climate change, but keeps water demand scenarios and water allocation policy the same as the Baseline.
- Option A: This option simulates economic and population growth that increases downstream urban water use and river water demands by 30% and 10%,

respectively. Water for agriculture was also projected to increase by 10% due to intensive cultivation and need for food security, as per government projections. This was relatively estimated based on the government reports including TDARD (2017), TPPA (2015) and NQCP (2021). The water level for recreation and priority coefficients would be kept the same as the baseline.

Table 4.2. The combination of future downstream water demand scenarios, water allocation policies and BMP.

		Options		
		Baseline	**BL0**	**A**
Water demand Scenarios	*Urban use*	Historical data	+0%	+30%
	Agricultural use	Historical data	+0%	+10%
	Downstream river	Historical data	+0%	+10%
Water allocation Policies	*Minimum water Level for tourism (Mcm)*	≥55	≥55	≥55
	Priority coefficients: Agriculture: a	50%	50%	50%
	Downstream river: b	0%	0%	0%
BMP	*Application of BMP*	No BMP	No BMP	No BMP

(+) and (–): Increase and decrease in water demand, respectively; (≥): At least.

Based on the simulation of options under land use and climate change scenarios (Table 4.3), the impact of water allocation policies, land use and climate change on the RRV of reservoir water supply were assessed. The study specifically considered the impact of combined land use and climate change on the RRV of reservoir by comparing the baseline with Option BL0 and A.

Table 4.3. Combined land use and climate change with water allocation options.

Combined land use and climate change			**Name of climate scenarios GCM-RCP**	**Water allocation options considered- under land use and climate change scenario**	
Land use	Climate change scenarios				
	GCM	*RCP*			
LU-S1	CCSM4	4.5	CCSM-M	BL0	A
		8.5	CCSM-H	BL0	A
	GFDL-CM3	4.5	GFDL-M	BL0	A
		8.5	GFDL-H	BL0	A
LU-S2	CCSM4	4.5	CCSM-M	BL0	A
		8.5	CCSM-H	BL0	A
	GFDL-CM3	4.5	GFDL-M	BL0	A
		8.5	GFDL-H	BL0	A

4.2.2.5. Determining reservoir storage in future

The baseline used historical rainfall data (2004-2013) and the 2014 land use map, while the future land use scenarios in 2100 used data generated by the GCMs (CCSM4 and GFDL-CM3) under the two RCPs 4.5 and 8.5. Over the period from 2014 to 2100s,

sediment accumulation in the reservoir will attenuate the storage capacity. It is assumed that the changes in land use and climate between the baseline and future scenarios will take place linearly. The storage of the reservoir was thus interpolated between the baseline and the future scenarios to determine the storage value before running optimisation simulations for 10 years, thereby comparing the results obtained with the 10-year baseline. The reservoir storage was estimated until 2093 and the simulations were then run for 10 years from 2094 to 2103. The accumulated sedimentation was, therefore, computed by the following equations:

$$Sed_{2093} = S_{Original} - \Delta S_0 - \sum_{1}^{8} (\Delta S_t)\,;\, t = 1, 2, \ldots, 8. \tag{4.2}$$

$$\Delta S_t = \Delta S_0 + t \times \left(\frac{\Delta S_{Simulation} - \Delta S_0}{T} \right) \tag{4.3}$$

Where, Sed_{2093} is the reservoir storage computed until 2093, $S_{Original}$ is the original reservoir storage (175 Mcm), T is the number of 10-year periods between the reference period (2004-2013) and simulated period during 2100s (T = 9), ΔS_t is the sedimentation generated during the 10-year period t^{th}, $\Delta S_{Simulation}$ is the total sedimentation created for 10-year simulation period (2100s) under the combination of land use and climate change scenarios, ΔS_0 is the total sedimentation generated for reference period (2004-2013). $\Delta S_{Simulation}$ and ΔS_0 were calculated by SWAT.

4.2.2.6. Reservoir performance indicators

Performance indicators are essential to assess operation periods of water resource systems (Hashimoto et al., 1982; Loucks et al., 2017). The indicators used in the study were:

1. *Reliability* (Reli): The ratio between water volume supplied over total volume demanded. This indicator shows an overview of reliability in water supply (Jain et al., 2008). A high value for this indicator is desired.

2. *Resilience* (Resi): This indicator shows the speed of recovery from an unsatisfactory condition or failure state (out of constraints). A high value for this indicator is desired.

3. *Vulnerability* (Vuln): The indicator aims to describe a statistical measure of the extent or duration of failure if a failure occurs. A low value for this indicator is preferred.

The calculation of Resilience and Vulnerability is expressed in Appendix C.

4. *Water spillage*: is the total of excess water spilled through the spillway.

4.3. Results

4.3.1. Change in climate, water inflows, and sediment inflows under land use and climate change scenarios

The calibrated parameter ranges were applied in SWAT-CUP to run simulations for the baseline land use under historical climate, and for the possible LU-S1 and LU-S2 under two GCMs and two RCPs. In the reference baseline period (BL) (2004-2013), the wet season often lasts from May to October, and the rest of the months represent the dry season. In contrast, scenarios CCSM-M and CCSM4-H generated average 34.5 mm/month and 85.8 mm/month greater rainfall from May to Aug and 10 mm/month and 25 mm/month lower rainfall in the Feb to Apr period, respectively. GFDL-M and GFDL-H created more rainfall than the reference period in both wet (by 35 and 89 mm/month) and dry seasons (by 10 and 25mm/month), respectively (Figure 4.4, Table 4.4). The increase of annual average rainfall under GFDL-H is the highest at 36.4% compared to the lowest increase under CCSM-M (6.8%) (Table 4.4). These increases are within the expected range investigated by MONRE (2016). Regarding temperature, the average minimum temperature of CCSM4 and GFDL-CM3 under Medium emissions rises by 9%, while that under High emissions increases by 22.3% (Table 4.4). All scenarios generated higher solar radiation than the baseline. GFDL-H produces the largest increase in solar radiation, by 10.8%.

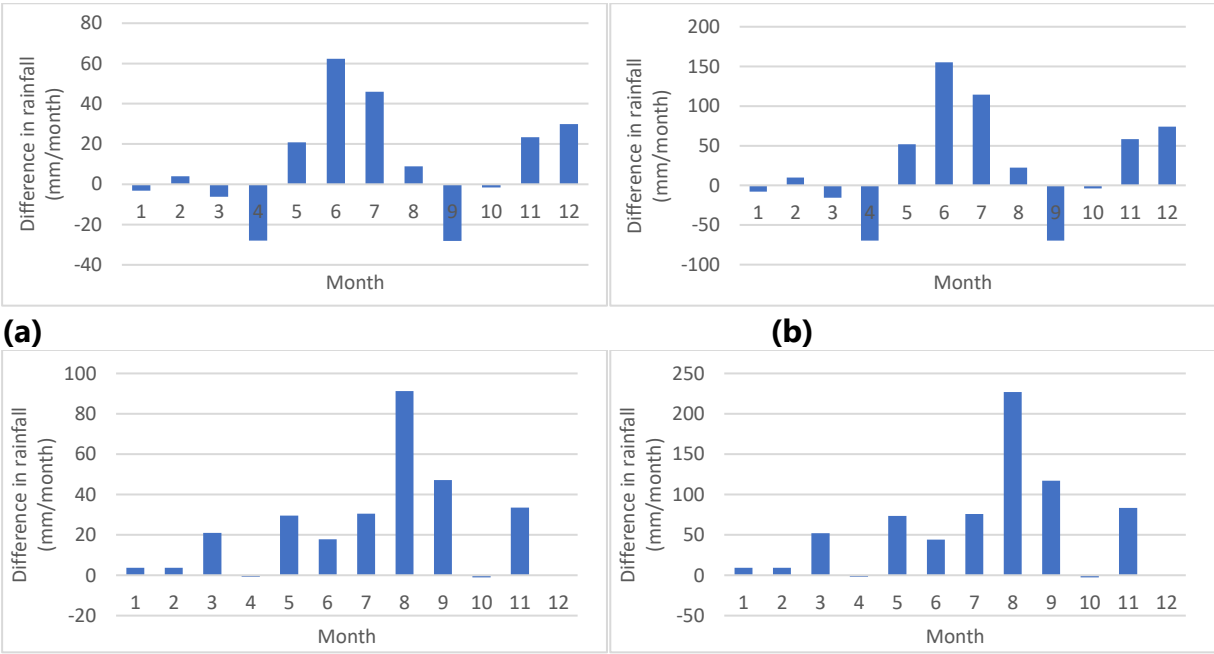


Figure 4.4. Change in future rainfall compared with the BL under CCSM-M (a), CCSM-H (b), GFDL-M (c) and GFDL-H (d).

Table 4.4. Changes in rainfall, temperature, and solar radiation under GCMs and RCPs.

Climate factors	(2004 – 2013)	2100s			
	Baseline (BL)	CCSM-M	CCSM-H	GFDL-M	GFDL-H
Rainfall (mm) (Annually average)	*1883.01*	2011.2 *+6.8%*	2201.5 *+16.9%*	2159.2 *+14.7%*	2569.3 *+36.4%*
Temperature (°C) Average Max - Min	*27.1 18.8*	28.3 20.5	30.2 23.0	28.7 20.5	31.2 22.9
Solar radiation (MJ/m^2) (Annual average)	*5225.3*	5386.3	5625.4	5453.8	5793.1

Under all GCMs and RCPs, LU-S2 generated insignificantly higher water inflows than LU-S1 while sedimentation created by LU-S2 was much larger than LU-S1 and BL (Table 4.5). Compared with the BL, both CCSM4 and GDDL-CM3 under RCP 4.5 and 8.5 produced approximately 25% and 50% higher water inflows in wet seasons, respectively; the expected sediment inflows under LU-S2 and GFDL-H, however, were the highest (1.95 Mcm/year) because this scenario has the largest transition from forest areas to the agricultural areas, and the change occurs near the reservoir (Chapter 3). In contrast, the LU-S1 under GFDL-H, with the 3% larger forest area and 2% lower agricultural areas, produces approximately 1 Mcm/year less sediment inflows compared with LU-S2 under GFDL-H, but still double that of the BL. In general, LU-S1 and LU-S2 under CCSM-M and CCSM-H generate 12% and 37% less water inflows than the BL during the three dry months (Feb, Mar, and Apr), while LU-S1 and LU-S2 under both GFDL-M and GFDL-H created 23% and 62% more water inflows during that drought period, respectively. The average sediment inflows closely follow the water inflows pattern (Table 4.5).

Table 4.5. Water inflows to the reservoir over a 10-year simulation (the median of 95PPU).

Scenarios	Baseline	LU-S1				LU-S2			
		CCSM-M	CCSM-H	GFDL-M	GFDL-H	CCSM-M	CCSM-H	GFDL-M	GFDL-H
Annual average water inflows (m^3/s)	15.49	17.34	19.66	19.52	24.67	17.39	19.71	19.56	24.72
Average water inflows in wet seasons (m^3/s)	26.0	29.2	32.6	32.5	40.6	29.37	32.75	32.67	40.73
Average water inflows in Feb, Mar, and Apr (m^3/s)	3.7	3.3	2.7	4.8	6.0	3.32	2.64	4.81	5.95
Average sediment inflows (Mcm/year)	0.5	0.64	0.78	0.72	1.02	1.27	1.50	1.40	1.95
Average sediment inflows in wet seasons (10^3 m^3/month)	86.6	108.8	127.2	120.1	164.5	218.6	250.1	234.2	319.8
Average sediment inflows in Feb, Mar, and Apr (10^3 m^3/month)	10.5	8.6	4.7	18.0	23.1	82.2	677.8	105.5	127.4

4.3.2. Calculation of accumulated reservoir storage under future climate and land use change

Based on equations (4.2) and (4.3), the reservoir storage was projected to decline from 175 Mcm in 2004 to 113.8 Mcm and 103 Mcm in 2095 under LU-S1 and GFDL-H and LU-S1 under CCSM4-H, respectively. The storage under LU-S2 and GFDL-H and LU-S2 under CCSM4-H would significantly decrease to 81 Mcm and 60 Mcm, respectively (Table 4.6). The future reservoir storage for each land use and GCM scenario under RCP4.5 is from 30 to 40 Mcm greater than that under RCP8.5. LU-S1 under CCSM4-M generates the lowest sedimentation; the future storage is, therefore, the highest, at 120.6 Mcm.

Table 4.6. Projected reservoir storage in 2093 under combined climate and land use change.

Climate change scenarios	Reservoir storage (Mcm)	
	LU-S1	LU-S2
CCSM-M	120.6	91.6
CCSM-H	113.8	81
GFDL-M	116.6	85.4
GFDL-H	103	60.2

4.3.3. The impact of land use and climate change on the performance of the reservoir

Probabilistic simulations were carried-out over a period of 10 years to quantify the broader impact of land use change, climate change on reservoir performance under the baseline/ reference period (2004–2013), and future scenarios for the period between 2094-2103. It was hypothesised that changes in water demands, land use and climate could significantly affect the reservoir's performance indicators. The baseline was compared with Option BL0 and Option A (Table 4.2). In general, most future scenarios result in lower reliability, resilience, and greater vulnerability than the baseline (Figure 4.5), even though the future climate resulted in more rainfall, because of the decrease in the reservoir storage.

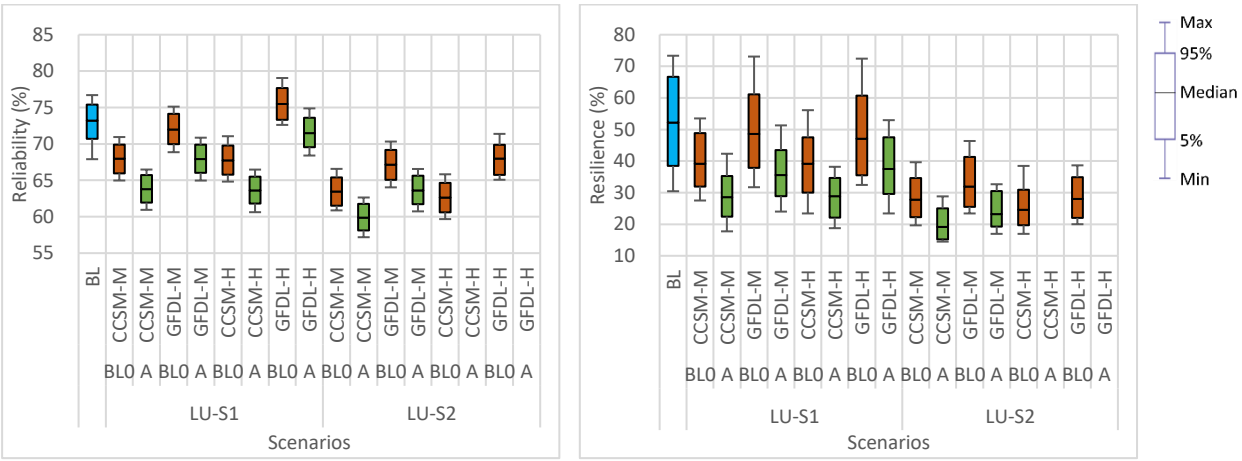
The baseline, consisting of historical data of land use, climate and water demands, generated the highest value of reliability, with a median value of 73.2% (Figure 4.5-a). LU-S2 provided from 4.5% to 7.5% lower reliability than LU-S1. The reliability under LU-S1 and GFDL-H of BL0 was 2.3% greater than that of the baseline, while that under GFDL-M of BL0 resulted in a median 1.3% lower than the baseline. Despite the lower storage than LU-S2 under CCSM-M of BL0, the LU-S2 under GFDL-M has 3.7% higher reliability, at a median 67.1%. LU-S2 under GFDL-H of BL0 with the lowest reservoir storage (60.2 Mcm) had a reliability of 68%.

Resilience values under all future scenarios are lower than the baseline (median of 52%) (Figure 4.5-b). LU-S2 under CCSM-H and GFDL-H for the BL0 simulation provide the lowest resilience, at a median 24% and 28%, respectively while resilience values of LU-S1 under CCSM-H and GFDL-H for BL0 are higher, with a median of 39% and 47%, respectively. LU-S2 always creates lower resilience than LU-S1.

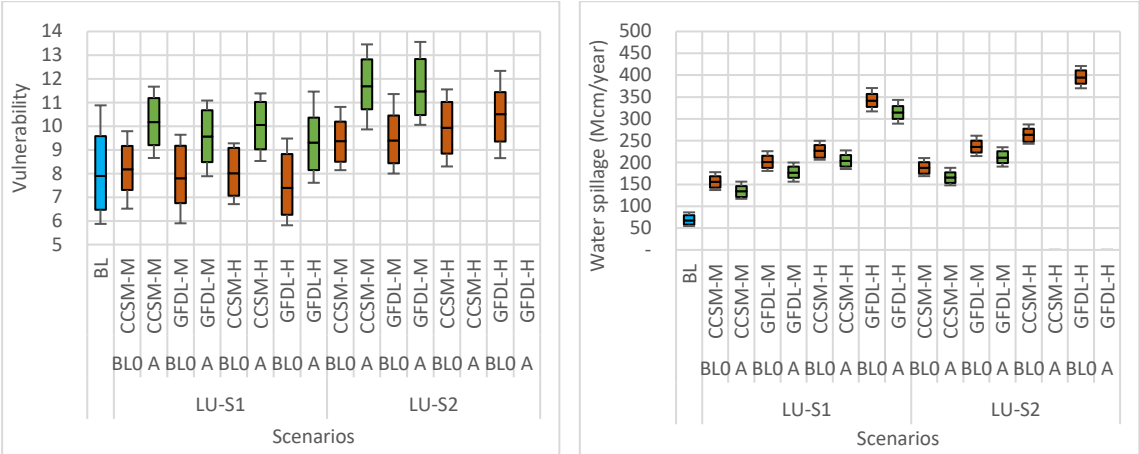
Vulnerability is in the opposite direction of reliability and resilience (Figure 4.5-c). The vulnerability of the baseline, with a median of 8, is lower than most scenarios. The resilience values generated by CCSM4 and GFDL-CM3 under Medium emissions and High emissions with LU-S1 have a median of around 8, while those with LU-S2 are more severe, with a median around 10. LU-S2 always generates higher vulnerability than LU-S1.

The water spillage under GFDL-CM3 is always greater than that under CCSM4 and the baseline (Figure 4.5-d). LU-S1 under GFDL-H and GFDL-M for BL0 generates a median of 314 and 200 Mcm/year, respectively, compared to 67.4 Mcm/year for the baseline, while LU-S2 under GFDL-H for BL0 can provide 400 Mcm/year in median. This means that the excessive water in wet seasons under all scenarios is expected to be very high, from 156 to 400 Mcm/year.

In the future, water demands will inevitably increase, and they are expressed by Option A. The results showed that increasing water demands in Option A made the reliability and resilience decline by approximately 4% and 10%, respectively compared with BL0, and increase the vulnerability by 2 (Figure 4.5). Furthermore, the reservoir failed to meet the minimum water level requirement for tourism in Option A under LU-S2 and CCSM-H, and under LU-S2 and GFDL-H due to extremely low storage, at 81 Mcm and 60.23 Mcm, respectively. The RRV and water spillage in these two cases were thus not determined.



(a) (b)



(c) (d)

Figure 4.5. Impact of climate, land use change, and water demands on the Reliability (a), Resilience (b), Vulnerability (c) and Water Spillage (d) of the reservoir. Performance of Option A with LU-S2 under CCSM-H and GFDL-H were not computed because reservoir failed to meet the minimum water level requirement for tourism.

4.4. Discussion

4.4.1. Comparison of the RRV and water spillage under GCMs and RCPs with the baseline

The framework applied for the Nuicoc watershed-reservoir system revealed that the combined land use and climate change had negative effect on reservoir's performance indicators. Although scenarios generated more water inflows to the reservoir compared with the baseline due to increasing rainfall and expanding urban areas, the increase in rainfall and conversion from forest to agricultural areas resulted in an increase in soil erosion within the watershed. This is similar to the findings of the study conducted by Khoi et al. (2014) in Vietnam where land use and climate change have the same trend. Sediment transported into the reservoir will reduce water storage over the long-term as indicated and Munthali et al. (2011). Under climate change scenarios, the LU-S2, which provided the highest reservoir sedimentation would therefore generate lower reliability and resilience, and create higher vulnerability in water supply than the LU-S1 scenario and the baseline.

More water spillage was observed under combined land use and climate change scenarios, particularly LU-S2 under GCMs (Figure 4.5). More run-off due to higher rainfall leads to greater sediment inflows (Phan et al., 2011), thereby making the reservoir storage decrease. We found that greater water inflows in wet season into a smaller reservoir storage (e.g., Option BL0) will result in significantly larger water spillage (3-8

times than that in the baseline). This subsequently generates higher risk of flooding events in downstream regions or higher risks or dam breaks.

The study area was projected to have much more rainfall under the very conservative scenario (High emissions) than the realistic scenario (Medium emissions). The high emission scenario combined with land use change significantly reduced the reservoir water supply. Although climate change is a global issue, government agencies in Vietnam should make strong commitments to replace fossil fuels with green energy, and apply new technologies to mitigate excess emissions.

It is important to note that this study simulated changes in land use within the reservoir watershed, but it did not consider the impact of change in water demands due to urbanisation and expanding agricultural areas. Although the change in water demand may be relatively small, this needs to be considered in future studies as the increase in upstream urban or agricultural areas may affect the reservoir reliability.

4.4.2. The role of RRV indicators in this case study

The results showed that some scenarios, such as LU-S1 under GFDL-H in Option A, provided nearly the same reliability as the baseline (with a median of 72.5%) as these scenarios created much more rainfall and urban areas than the baseline. The resilience and vulnerability under this scenario are, however, worse. Although the reliability describes the probability that the system is in a satisfactory state (satisfying water demand), the resilience is an indicator of how fast a reservoir recovers and returns to a satisfactory state, and the vulnerability describes how adverse the unsatisfactory state is (Hashimoto et al. (1982); Loucks et al. (2017). The difference in RRV indicators suggests that the reservoir under future scenarios will not recover as quickly to a satisfactory state as the baseline, and that the water shortages will happen regularly during the dry season. This shows the importance of using supplemental indicators of resilience and vulnerability in the context of land use and climate change.

4.5. Conclusions

A modelling framework to quantify the impacts of land use and climate change on the reservoir RRV indicators was applied to the Nuicoc multi-purpose reservoir in Thainguyen, Vietnam. The results indicated that expanding urban areas and conversion from the forest areas to agriculture under GCMs and RCPs would generate more water inflows and sediment inflows to the reservoir. The increase in sediment flows generated

lower reliability and resilience, and higher vulnerability in the reservoir water supply, although precipitation was projected to increase significantly in the future. In addition, the reduced reservoir storage will likely cause an increase in downstream flood risk under combined climate and land use change.

This study determined the reservoir volume reduction over time by assuming linear changes in sedimentation between baseline conditions and future scenarios. To account for non-linear sedimentation, future research should aim to develop a methodology to dynamically simulate the reservoir sedimentation over time and include an envelope of uncertainty for those simulations. It is also important to note that future water demands were simulated based on the government's short-term future plans and therefore these should be revised as plans change.

The results obtained from this study are valuable to local decision-makers, but the methodology adopted is broadly relevant for management of water demands, land use, and sedimentation under a wide range of uncertainties, and the scenarios help to demonstrate how adaptation actions and mitigation policies can be implemented to reduce the impact of climate and land use changes on reservoir RRV.

Chapter 5 . WATER ALLOCATION POLICY MANAGEMENT ON FUTURE RELIABILITY, RESILIENCE AND VULNERABILITY OF RESERVOIR WATER SUPPLY

5.1. Introduction

Growing population, higher standards of living, increasing water demands, land use change and climate change have created pressure on available water resources in many geographical regions. Multipurpose reservoirs play an important role in providing water to a variety of users while also reducing the risk of water shortage (Goodarzi et al., 2013). Reservoir storage will be, however, attenuated over time due to sedimentation and soil erosion caused by land use (Nguyen et al., 2021; Shrestha et al., 2018), the water supply reliability is then negatively impacted. Climate change is also causing changes in precipitation, temperature and solar radiation which will impact water availability of reservoirs. Identifying possible impact of land use and climate change on the reliability of a reservoir in future followed by suggesting water management policies to increase reservoir water supply is essential for the decision making progress.

Chapter 4 showed that combined land use and climate change had great impact on the reliability, resilience, and vulnerability of the Nuicoc reservoir in Vietnam. Water allocation policies should be, therefore, formulated by the reservoir operator to improve the reservoir reliability under uncertainty in land use and climate change. Management options have been used to consider the reservoir performance. For example, Goodarzi et al. (2013) considered strategies using different priorities in water allocation for water demands, such as domestic-industrial use, agriculture and power plant, from the Doroudzan dam in Iran. They indicated that the reservoir reliability created by the different strategies changed from 30% to 74%, and that strategies having lower minimum allowable releases (lower priorities) for agriculture and power plant would generate higher reservoir reliability. Regarding the Segura River Basin in Spain, López-Ballesteros et al. (2019) used SWAT model to investigate the effectiveness of five BMPs (contour planting, filter strips, reforestation, fertilizer application and check dam restoration) on sediment and nutrient reduction in the river. Check dam restoration was indicated to be the most effective BMP with a reduction of 90% in sediment yield (S), 15% in total nitrogen and 22% in total phosphorus at the watershed scale, followed by reforestation (S = 27%). When BMPs were assessed in combination, the effectiveness improved (López-Ballesteros et al., 2019). Studies by Shrestha et al. (2021) and López-Ballesteros et al. (2019) highlighted

the importance of BMPs in the reduction of soil erosion that would be good for reservoir storage. Those previous studies have not, however, investigated the impact of management policies of watershed and water allocation on the reservoir reliability, resilience, and vulnerability in water supply under combined climate and land use change.

As the multi-purpose Nuicoc reservoir plays a significant role in the region and the reservoir has been impacted by land use change, climate change and growing water demands as described in Chapter 4, this chapter aims to consider management options to improve the reservoir water supply.

5.2. Material and Method

The study area of the Nuicoc watershed-reservoir system and the model setup including uncertainties considered, climate models, land use change scenarios, the determination of future reservoir storage, and performance indicators in this chapter were kept the same as in Chapter 4, with the exception of BMPs. The impact of management options consisting of BMPs, water allocation policies, and water demand scenarios, were investigated (Figure 5.1).

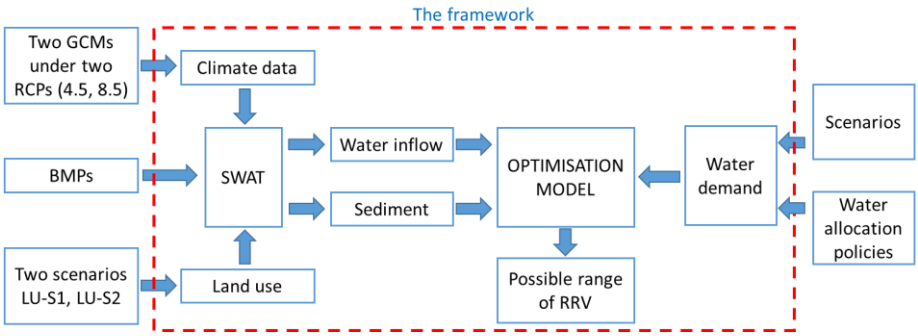


Figure 5.1. Model established for determining the possible range of RRV.

5.2.1. Application of best management practices (BMP) within the watershed

BMPs can be applied within the catchment to reduce soil loss and thus sedimentation of the reservoir. Erosion caused by rainfall and runoff is calculated by the Modified Universal Soil Loss Equation (MUSLE) (Williams et al., 1975) in SWAT (Equation (5.1)):

$$Sed = 11.8 \times (Q_{surf} \times q_{peak} \times area_{hru})^{0.56} \times k_{USLE} \times C_{USLE} \times P_{USLE} \times LS_{USLE} \times CFRG \qquad (5.1)$$

where Sed is the sediment yield on a given day (metric tons), Q_{surf} is the surface runoff volume (mm/ha), q_{peak} is the peak runoff rate (m^3/s), $area_{hru}$ is the area of the HRU (ha), k_{USLE} is the soil erodibility factor, C_{USLE} is the cover and management factor, P_{USLE} is the support practice factor, LS_{USLE} is the topographic factor and CFRG is the coarse fragment factor. This study focused on the P_{USLE} factor as it represents the soil loss fraction with a

specific support practice. P_{USLE} values range from 0 to 1 based on the applied support practices. Key support practices to reduce erosion in a watershed include contour tillage, strip cropping on the contour, and terrace systems (Neitsch et al., 2011). Strip-cropping is a practice in which contoured strips of sod are alternated with equal-width strips of row crop or small grain and terracing is used to modify the slope and length of the slope. Recommended values for contour strip-cropping and other BMP's are widely available in literature. In this case study, the application of BMP's with a range of P factors (Table 5.1) were considered to mitigate soil erosion.

Table 5.1. BMP considered in this study by using P_{USLE} value.

BMP	P_{USLE}
No BMP	1
BMP1	0.25
BMP2	0.4
BMP3	0.7

5.2.2. Water allocation options

In long-term future, there will be significant changes in water demands, water allocation policies and BMPs, leading to high uncertainty. Water allocation options are defined as combinations of those factors to quantify the uncertainty. Water demand scenarios express the change in future water use of each sector. Water allocation policies include a minimum water level for tourism and sector priority coefficients required by the government. A variety of priority coefficients for downstream agriculture and river water supply were considered based on equation (4.1) in Chapter 4.

Water allocation options (Table 5.2) are expressed as follows:

- The baseline: Historical water demand was used for each sector. Minimum demand priorities were applied, with priority coefficients for downstream agriculture and river set at 50% and 0% (Priority 1), respectively. BMPs were not applied. The reservoir was kept to the minimum water level at 55 Mcm in May for recreational purpose to comply with current government policy. The simulation will stop if the reservoir cannot satisfy the recreational requirement.
- Option A: As described in Chapter 4, this option increases downstream urban water use and river water demands by 30% and 10%, respectively. Water for agriculture was also projected to increase by 10%. The water level for recreation and priority coefficients would be kept the same as the baseline.

- Option B: This option has the same water demand scenario as from Priority 1. In addition, BMP2 was applied to agricultural areas within the watershed by using the P_{USLE} value of 0.4 (Table 5.1).
- Option C: This option has the same increase in water consumption of downstream users as Option A. The requirement for tourism water level is, however, reduced from 55 Mcm to 33.5 Mcm. BMP's are not applied in this option.
- Option D: Water level for recreation, downstream urban areas and river are the same as Option C. However, the water demand for agriculture will decrease by 20% (TDARD, 2017) as the downstream agricultural areas are replaced by downstream urban areas, or if flooding irrigation methods are converted to other water-saving irrigation methods, or a choice of crops which require less water.
- Option E: This option has the same water demands as Option A except for the difference in the priority coefficients for agriculture and downstream river, in which a = 75% and b = 25% (Priority 2). BMP's are not applied in this option.
- Option F: This option is the same as Option E, but BMP2 was applied for agricultural areas within the watershed.
- Option G: This option combined the application of BMP2, the decrease in water demand scenarios, and water allocation policies.

Table 5.2. The combination of future downstream water demand scenarios, water allocation policies and BMP.

		Baseline	Options						
			A	B	C	D	E	F	G
Water demand Scenarios	*Urban use*	Historical data	+30%	+30%	+30%	+30%	+30%	+30%	+30%
	Agricultural use	Historical data	+10%	+10%	+10%	–20%	+10%	+10%	–20%
	Downstream river	Historical data	+10%	+10%	+10%	+10%	+10%	+10%	+10%
Water allocation Policies	*Minimum water Level for tourism (Mcm)*	≥55	≥55	≥55	≥33.5	≥33.5	≥55	≥55	≥33.5
	Priority coefficients: Agriculture: a	50%	50%	50%	50%	50%	75%	75%	50%
	Downstream river: b	0%	0%	0%	0%	0%	25%	25%	0%
BMP	*Application of BMP*	No BMP	No BMP	BMP2	No BMP	No BMP	No BMP	BMP2	BMP2

(+) and (–): Increase and decrease in water demand, respectively; (≥): At least.

Based on the simulation of options under land use and climate change scenarios (Table 5.3), the impact of water allocation policies, land use and climate change on the reliability of reservoir water supply were assessed. The following were specifically considered:

(1) impact of water allocation policy (through priority coefficients) by comparing the Options A and E,

(2) impact of minimum requirement for tourism by comparing Options A and C,

(3) impact of change in downstream demands by comparing Options C and D,

(4) impact of applying BMPs by comparing Options A and B, E and F,

(5) impact of combined water demand scenarios, policies, and BMP's by comparing Options A and G, and

(6) sensitive analysis of BMPs on the reliability

Table 5.3. Combined land use and climate change with water allocation options.

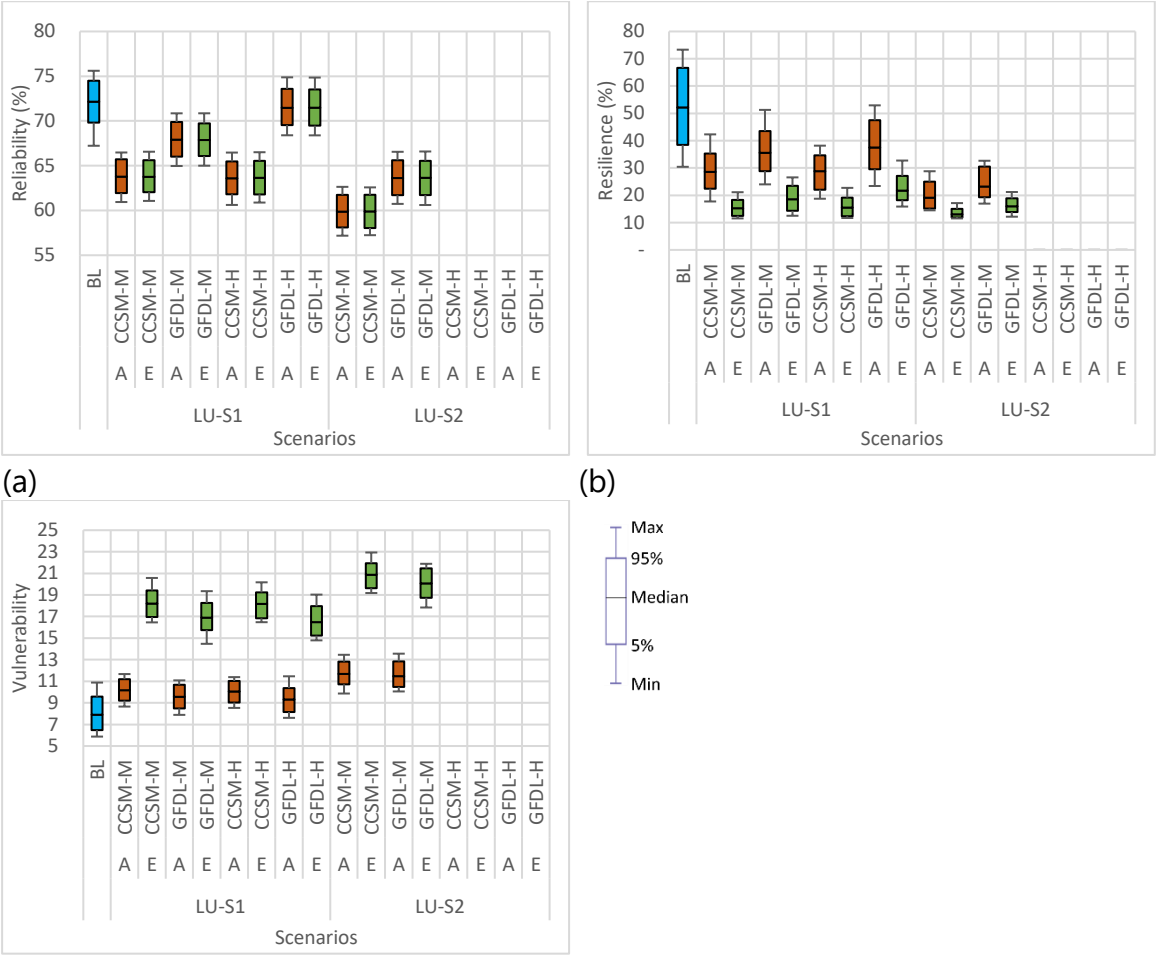
Combined land use and climate change			**Name of climate scenarios GCM-RCP**	**Water allocation options considered-under land use and climate change scenario**						
Land use	Climate change scenarios									
	GCM	*RCP*								
LU-S1	CCSM4	4.5	CCSM-M	A	B	C	D	E	F	G
		8.5	CCSM-H	A	B	C	D	E	F	G
	GFDL-CM3	4.5	GFDL-M	A	B	C	D	E	F	G
		8.5	GFDL-H	A	B	C	D	E	F	G
LU-S2	CCSM4	4.5	CCSM-M	A	B	C	D	E	F	G
		8.5	CCSM-H	A	B	C	D	E	F	G
	GFDL-CM3	4.5	GFDL-M	A	B	C	D	E	F	G
		8.5	GFDL-H	A	B	C	D	E	F	G

5.3. Results

Climate and land use change will have a considerable impact on the RRV and water spillage of the reservoir. The results show a reduction in water supply although there will be more rainfall in future. Specific results of the effect of policies and BMPs on RRV are presented below.

5.3.1. Impact of changes in minimum requirement water allocation

A comparison between Option A and E was done to study the effect of water demand priorities. Higher minimum demand priorities (Equation (5.1)) for downstream agriculture and river were set to a = 75% and b = 25% (Priority 2) in Option E. This means that agriculture and river downstream require more water in dry seasons. The reliability in this case is almost the same as Option A with a = 50%, b = 0% (Priority 1). The big difference is in the resilience and vulnerability as the resilience in Option E is 28% lower than that under Option A and the vulnerability in Option E is approximately a value of 8 higher (Figure 5.2). Results show that selection of water allocation policy will significantly impact on the resilience and vulnerability of the reservoir.



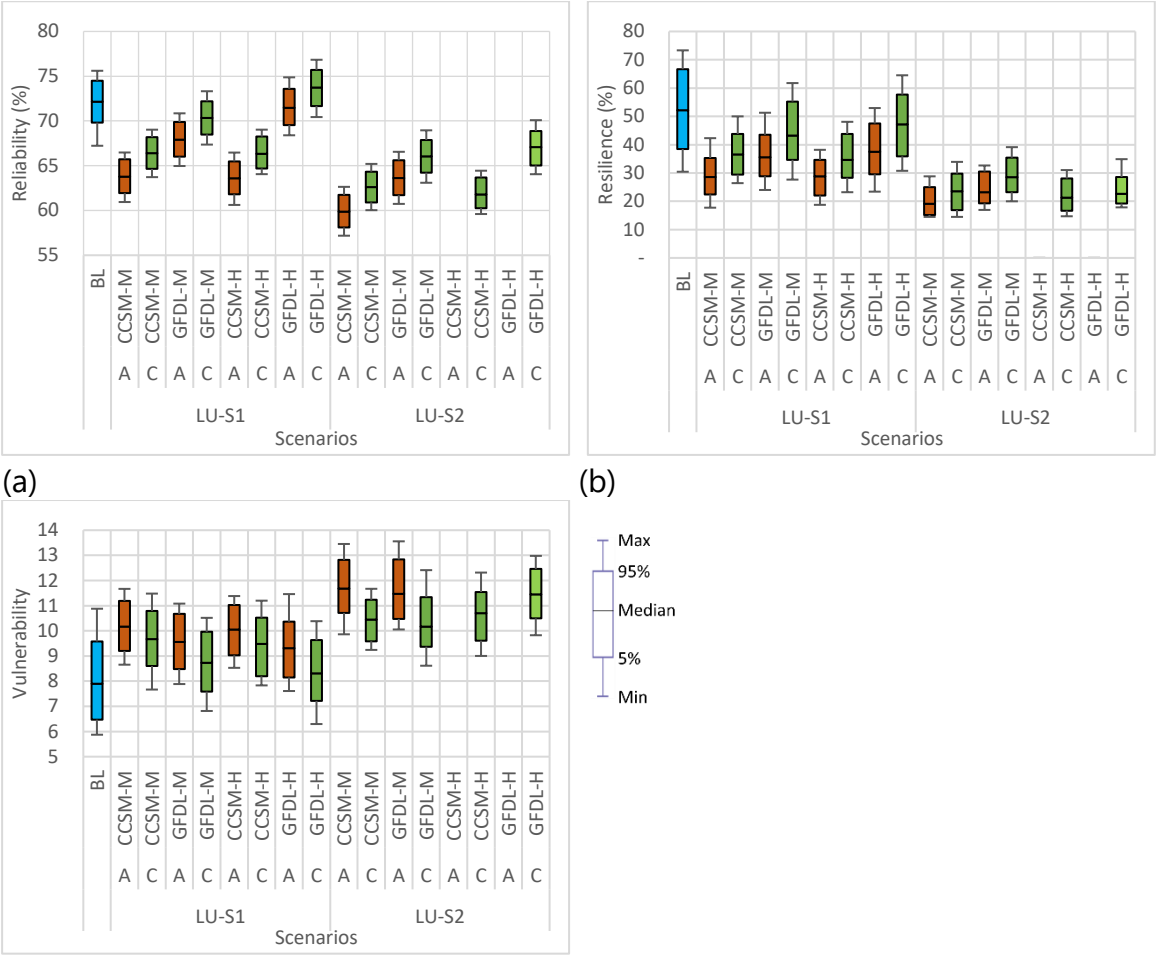
(a) (b)

(c)

Figure 5.2. Comparison of the impact of minimum requirement water allocation on the reliability (a), resilience (b) and vulnerability (c) between Option A and E. Performance of Options A and E with LU-S2 under CCSM-H and GFDL-H was not shown because the tourism constraint is violated.

5.3.2. Impact of the reduction in minimum requirement of water level for tourism

The decrease of the recreational (tourism) water level in May is an option to consider in the future as the reservoir storage is attenuated. The effects of a reduction of minimum water level for recreation in May was simulated by comparing Option A (baseline with 40 m (55 Mcm) water level in May) with Option C (38 m (33.5 Mcm) water level in May) for all climate and land use change scenarios (Table 5.2, Figure 5.3). The water supply reliability under all scenarios for Option C increases by 2.5% compared to Option A (Figure 5.3-a). LU-S1 under GFDL-H provides 1.5% greater reliability than the baseline; the resilience and vulnerability are, however, significantly worse than the baseline (by 5% and 0.42, respectively) (Figure 5.3-b, c). In Option C, scenario LU-S2 under CCSM-H, and scenario LU-S2 under GFDL-H the tourism constraint was not violated.



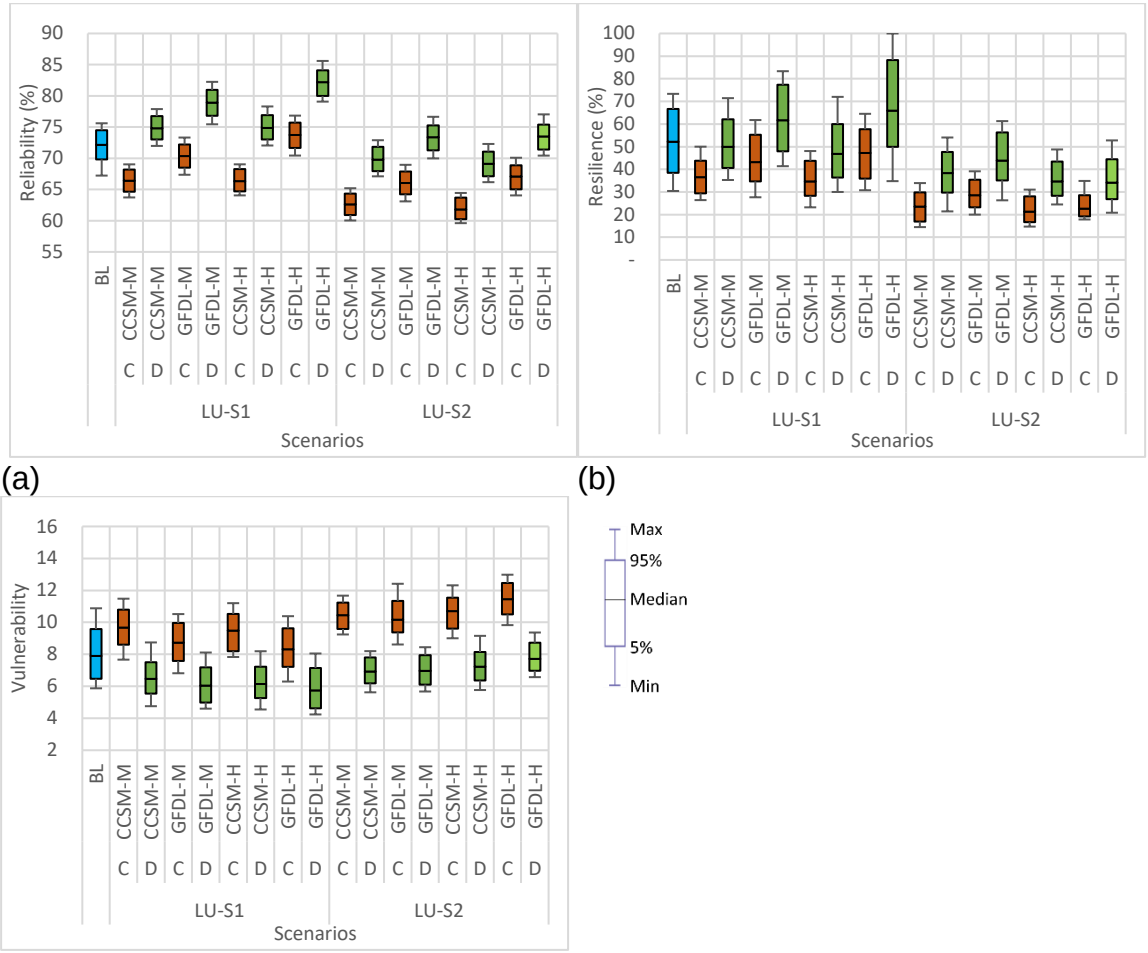
(a) (b)

(c)

Figure 5.3. Comparison of the impact of recreational minimum water level on the reliability (a), resilience (b) and vulnerability (c) between Option A and C.

5.3.3. Impact of reduction in water demand for agriculture and minimum requirement of water level for tourism

A comparison between Option C and D was conducted to determine the impact of reduction in water demand for agriculture and minimum requirement of water level for tourism (Figure 5.4). All scenarios with LU-S1 under two GCMs and RCPs in Option D generated from a median 2.5% to 10% higher reliability than the baseline. The LU-S1 under GFDL-H created the highest reliability, with a median of 82.2%. In addition, the all simulations with LU-S1 also have better resilience and less vulnerability than the baseline and the simulations with LU-S2. Although the LU-S2 under GFDL-M and GFDL-H provides 1% better reliability than the baseline, the resilience values of those are 8-18% lower.



(a) (b) (c)

Figure 5.4. Comparison of the impact of reduction in downstream water demands on the reliability (a), resilience (b) and vulnerability (c) between Option C and D.

5.3.4. Impact of the application of the best management practices (BMPs) for agricultural areas

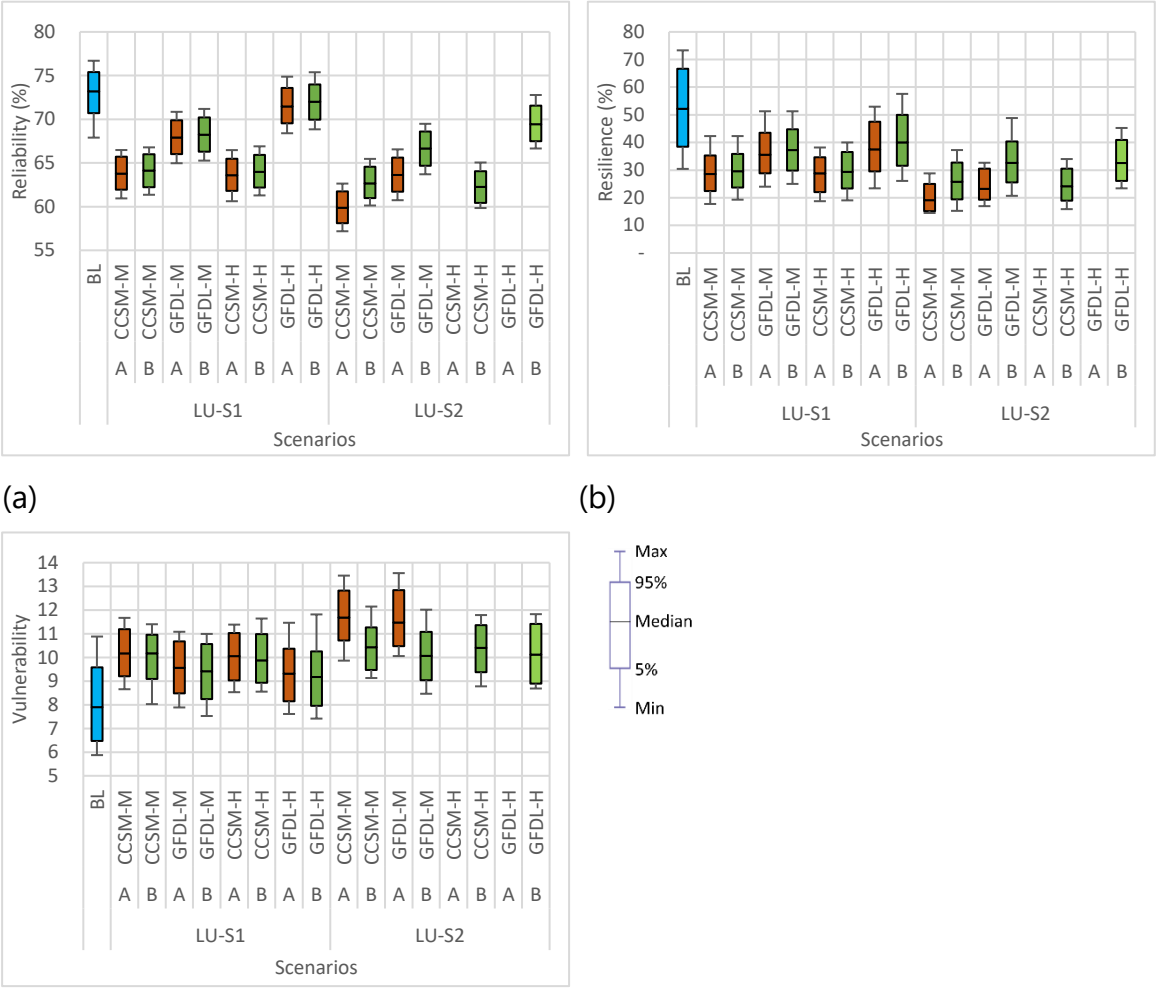
After the application of BMPs, there was an increase in the reservoir storage under all scenarios, particularly under LU-S2 (Table 5.4). Compared to scenarios without BMP (Option A), storage under scenarios with BMP2 (Option B) increases by 2-3% for LU-S1, and 20-50% in median for LU-S2.

Table 5.4. Reservoir storage with the application of best management practices.

GCM	RCP	LU-S1			LU-S2			
		No BMP	BMP1	BMP2	No BMP	BMP1	BMP2	BMP3
CCSM4	4.5	120.58	123.5	122.9	91.62	116.7	111.81	
	8.5	113.84	117.2	116.5	81	109.3	103.69	
GFDL-CM3	4.5	116.60	119.7	119.1	85.35	112.4	107.12	96.30
	8.5	103.01	107.3	106.5	60.23	97.2	89.86	

With Option B, scenarios using LU-S1 with BMP2 (LU-S1_BMP2) created 0.5% greater reliability than the case without BMPs (Option A), and LU-S2_BMP2 resulted in 2-3% greater reliability. LU-S2_BMP2 produces 5% higher resilience and 2% lower vulnerability

than that without BMPs. In addition, the LU-S2 under CCSM-H and LU-S2 under GFDL-H will not violate the recreational policy (Figure 5.5).



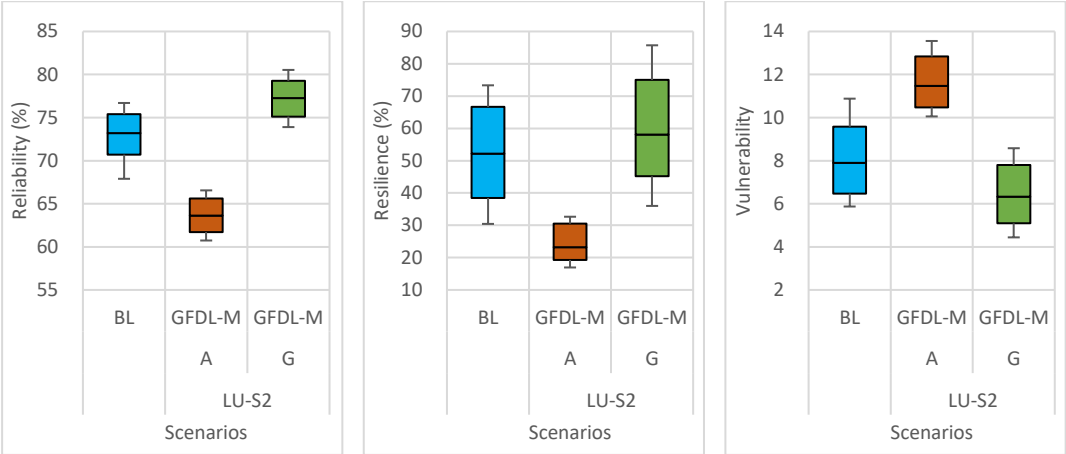
(a) (b)

(c)

Figure 5.5. Comparison of the impact of BMP on the reliability (a), resilience (b) and vulnerability (c) between Options A and B.

5.3.5. Combination of water demands scenarios, water allocation policies and application of BMP.

The effectiveness of the combination of water demands scenarios, water allocation policies and application of BMP (Option G) was investigated under LU-S2 and GFDL-M. Option G was compared with Option A. The reliability and resilience of Option G were the highest at 77% and 59%, respectively, while those of Option A were approximated at the median of 64% and 22%, respectively. The vulnerability of Option G was, thus, the lowest, at around 6 in median.

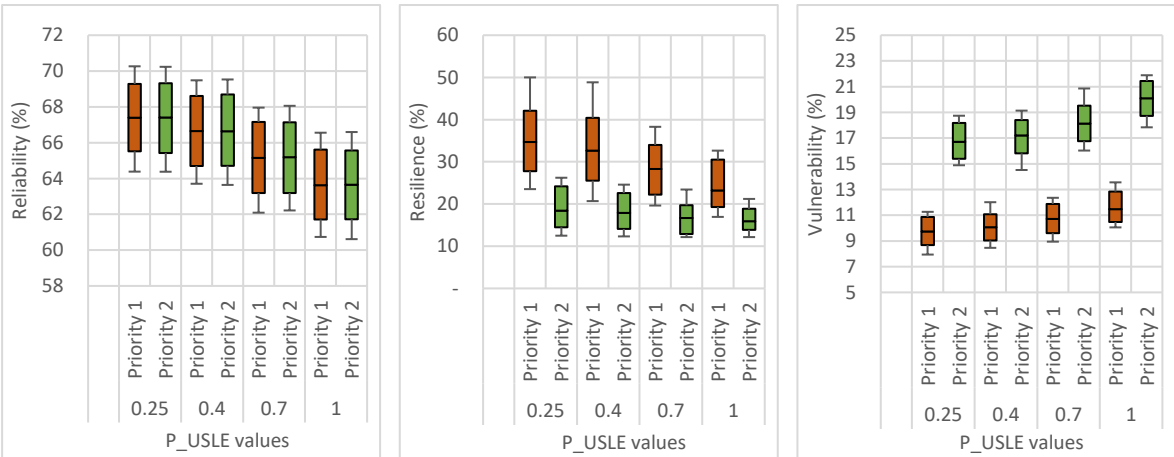


(a) (b) (c)

Figure 5.6. Comparison of the impact of combined water demands scenarios, water allocation policies and application of BMP on the reliability (a), resilience (b) and vulnerability (c) between Option A and G.

5.3.6. Sensitive analyses of BMPs for LU-S2 under GFDL-M

The sensitivity of BMPs was studied by altering P_{USLE} values from 1 to 0.25 (Table 5.1) and priority coefficients. The reliability values of Priority 1 (a = 50%, b = 0%) and Priority 2 (a = 75%, b = 25%) were similar and changed from 63.5% to 67.5%. The resilience of Priority 1 significantly increased from 23.5% to 35% while there was a small increase of Priority 2 from 16% to 18%. The Vulnerability declined through the range of P_{USLE}, from 11.5 to 9.5 for Priority 1, and from 20 to 16.5 for Priority 2. The change in RRV does not appear to be linear.



(a) (b) (c)

Figure 5.7. The impact of BMP ranges and two priority coefficients on the reliability (a), resilience (b) and vulnerability (c).

5.4. Discussion

Water allocation policy has a large impact on RRV. When policy was changed from Priority 1 to 2 to allocate more water to downstream users, it became more difficult to satisfy water demands constraints. The resilience of Priority 2 was much lower than that of Priority 1 while the vulnerability of the former was much greater.

Simulations also indicated a policy of decreasing minimum water levels for recreation in May increased the working reservoir storage and provided better reservoir water supply indicators under combined land use and climate change. The policy of reducing water levels for recreation in May, however, could be controversial and has to be weighed against the impacts on the tourism industry.

In addition, despite generating better reservoir indicators than the baseline (Option D), it is noticeable that the reduction in water demands in wet seasons could create much more water spillage for downstream areas (e.g., Under scenario LU-S2 and GFDL-M) (Item 5, Table S15 in Appendix B).

The application of BMPs for agricultural areas within the watershed was generally beneficial to the long-term operation of the reservoir, but the spatial targeting of BMPs was very important. Under the same GCMs and RCPs, BMPs applied for LU-S2 were observed to be more effective than for LU-S1 (Table 5.4). The spatial distribution of land uses within the reservoir watershed between LU-S2 and LU-S1 were the main reason for the impact of BMPs on reservoir storage. Many agricultural areas under LU-S1 and LU-S2 are distributed in the north of the watershed, but most sediment yield created by those areas will be deposited along the main stream, as indicated in Chapter 3. . Since the agricultural areas near the reservoir under LU-S2 (479 ha) was roughly five times that of LU-S1 (88 ha), the sediment yield under the former was approximately five times that under the latter (Chapter 3). This in turn helped LU-S2 have a greater increase in the reliability and resilience of the reservoir than LU-S1 (Figure 5.5). Thus, the importance of BMP in sediment reduction as mentioned in other studies (López-Ballesteros et al., 2019; Shrestha et al., 2021) should be underlined and prioritised for the agricultural areas near the reservoir which have a direct impact on its sedimentation.

The application of BMP combined with adequate water policy and water demand scenarios (Option G) enhance reservoir RRV indicators more than each option implemented individually (Figure 5.6). BMPs contribute to the reduction in reservoir sedimentation (Shrestha et al., 2021) while water allocation policies help to increase

working storage. In addition, the decrease in water demands, particularly in agricultural use, reduces pressure on reservoir water supply.

The study investigated the application of BMPs for agricultural areas only. Other land uses, including paddy fields and tea trees around the reservoir, should be also considered to mitigate sedimentation. Additionally, the study did not account for the uncertainty in sediment accumulation in the reservoir from the baseline to future period; however, the results reflected a relative change in reservoir storage between the two periods.

5.5. Conclusions

A proposed framework was applied to consider the impacts of water allocation policy management on the RRV indicators of the Nuicoc multi-purpose reservoir. The application of BMP's in the watershed to minimise erosion and reservoir sedimentation can have major long-term impact on water storage capacity, thereby increasing water supply and reducing spillage flood risk. Modifying allocation policies are also a viable tool to improve the reservoir RRV indicators. When allocation policies are combined with BMP's, the reservoir water supply can be improved beyond baseline conditions. It is important to note that future water demands were simulated based on the government's short-term future plans and therefore these should be revised as plans change.

Chapter 6 . CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

6.1.1. The framework for quantifying the reliability, resilience and vulnerability of reservoir water supply under uncertainty.

The modelling framework developed in this thesis contributes to the advancement of the scientific understanding about the impact of water allocation policy, land use and climate change on the reliability of a reservoir. The probabilistic optimisation approach implemented in the framework helps to determine the possible range of reservoir performance indicators based on optimisation analyses under uncertainties in water and sediment inflows, and water demands over the operational timeframe. The optimisation tool using the genetic algorithm helps the framework have greater reliability in obtaining the optimal solutions. In addition, the framework allows for water allocation policies and the application of BMPs to be simulated. The framework, which is not difficult to use, provides decision-makers with probabilistic information to help plan for the management of water resources, land uses and sedimentation. Despite having many benefits, the framework still has a number of limitations. Apart from higher computational cost, the framework makes some assumptions about distributions of monthly inflows within 95PPU, and about the relationship between water inflow and sediment inflows into the reservoir. In addition, the number of feasible combinations of inflows and water demands (n-value) should be also considered to balance the computational cost and the model accuracy. Furthermore, the impact of water quality issues due to expanding urban and agricultural areas were not included in the framework. The framework can be applied for other single watershed reservoir system to determine the RRV indicators under a broad set of uncertainties; however, the operation of multi-reservoirs has not been considered in the framework.

6.1.2. The impact of land use change and spatial distribution of land use

The framework applied for the Nuicoc watershed-reservoir system showed that the increase in urban areas and conversion from forest to agricultural areas through land-use scenarios could affect the reservoir's indicators over the long-term period. Soil erosion and sedimentation are the key long-term impacts on water availability of the reservoir as sediment accumulation will reduce the reservoir storage. This in turn decreases the water reliability. Furthermore, the importance of land-use distribution should be also highlighted

in the planning and managing of land-use as this has significant impact on the reservoir's performance indicators. Apart from attenuating the reservoir storage and mitigating water supply, increasing sedimentation due to land use changes will lead to more excessive water spillage in wet seasons and cause more risk of floods in downstream areas.

6.1.3. The impact of combined future land use and climate change

Under combined land use and climate change, more water and sediment inflows will be generated in the catchment of the Nuicoc multi-purpose reservoir. This in turn leads to poor reservoir indicators despite there being more rainfall in future. This means that if future land use and climate change happen as per the scenarios, the reservoir may witness a significant reduction in water supply and regular water shortages in dry seasons due to the decrease in working reservoir storage. In contrast, the downstream area will face higher risk of flooding events during wet seasons.

6.1.4. The impact of water allocation policies and application of BMP

As the accumulated sedimentation makes the reservoir water availability decreases, water allocation policy management, including priority coefficients and minimum water level for recreation, should be considered for improving the reservoir reliability. In addition, the application of BMPs is critical to mitigate soil erosion within the reservoir watershed as they have long-term influence on the reservoir operation. The spatial targeting of BMPs is also very important because BMPs placed closer to the reservoir in this case study seem to have greater impact than those placed farther away. This information is valuable to decision-makers when prioritising the location of BMPs within the reservoir watershed. These measures help to prolong the life of the reservoir, increase the capacity of flood protection, and increase reservoir water supply compared with the case without measures applied.

6.2. Recommendations for the management of watershed-reservoir system

Assessing the impacts of a broad set of uncertainties will help decision makers have adequate policies for the management of water resources, sedimentation, land-use, under climate change. These are key recommendations for improving reservoir performance in water supply and flood protection, mitigating water shortages and performing adaptation actions:

- The water allocation policies should be combined with the application of BMPs to promote the efficiency in reservoir operation under uncertainty in land use and climate change.
- Water-saving irrigation methods and crops should be considered to replace the downstream paddy fields, which are currently inefficient in water use. This can save water for other demands such as urban and recreational use.
- Land use planning should be carefully considered. The transition from forest to agricultural area near the reservoir should be avoided.
- Reservoir operators should be made aware of the higher risk of floods in downstream areas due to the great impact of combined land use and climate change.
- New small reservoirs should be constructed in the tributaries which run directly into the main reservoir. These can help decrease the flooding peak, reduce sedimentation for the main reservoir, and supplement water to the main reservoir in dry seasons.

6.3. Recommendations for future studies

To improve the modelling framework and application outcomes, future research is needed on these topics:

- Further studies in the Nuicoc watershed should include the impact of increasing upstream water demands due to urbanisation and expanding agricultural areas within the reservoir watershed.
- Investigating different types of BMPs on declining sediment yield in the reservoir watershed and their impacts on the reservoir indicators.
- Other indicators related to reservoir water quality such as nutrient and TSS should be included in the framework.
- Developing a methodology to dynamically simulate the reservoir sedimentation over time and the uncertainty for those simulations will be quantified.
- Applying the proposed framework to other watershed reservoir systems with different land use and climate change scenarios, water allocation policies and BMP.
- Developing a methodology to apply the framework for cascading reservoir systems as there is often a network of reservoirs within large watersheds.

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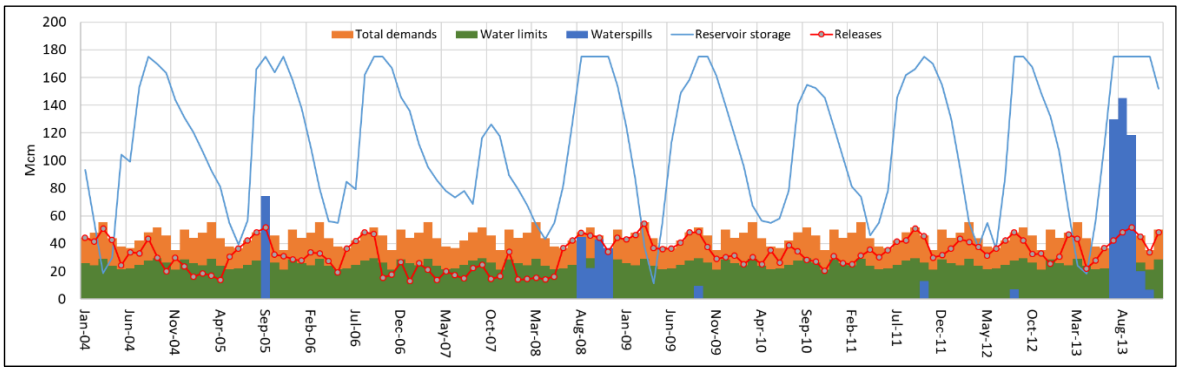
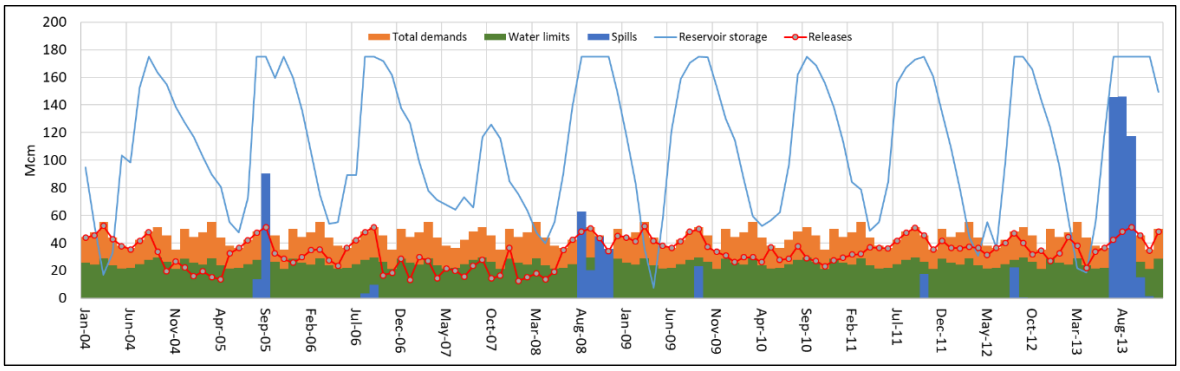
Appendix A

Table S1. List of calibrated ranges of parameters

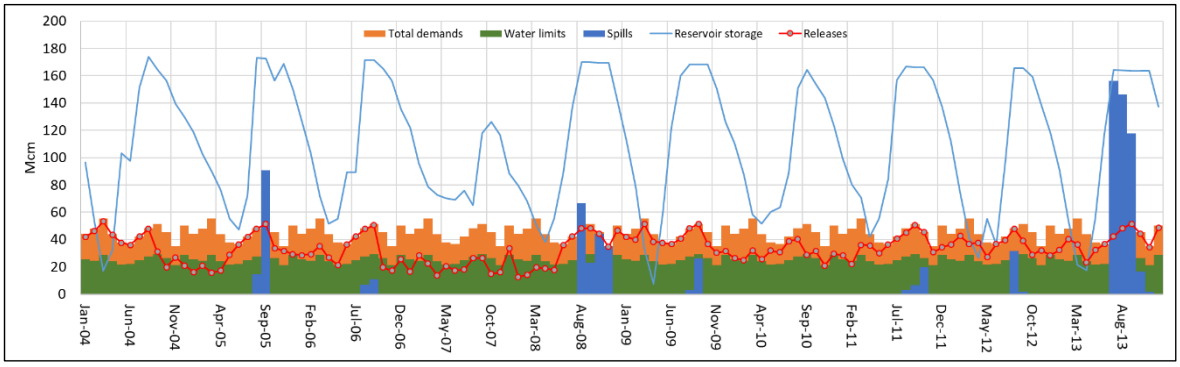
Parameter	Initial value/ range	Min	Max	Scaling type	Note
CN2	Depend on land use	- 0.21	0.09	r	Relative change in percent
ALPHA_BF	0 – 1	0.023	0.070	v	Replace the range of value
RCHRG_DP	0 – 1	0.008	0.67	v	Replace the range of value
GWQMN	0 – 5000	1466	4408	v	Replace the range of value
SOL_AWC	0.16	- 0.09	0.5	r	Relative change in percent



(a) Time series of reservoir operation when sediment was not considered – Baseline



(b) Time series of reservoir operation when sediment was not considered under S3



(c) Time series of reservoir operation when sediment was considered under S3

Figure S1. Time series of the reservoir over 10-year period

Table S2. t-test for the reliability when sedimentation was not included over 10-year simulations.

Independent sample t-test Reliability (%) Sedimentation not included			BL_NoSED		S1_NoSED		S2_NoSED		S3_NoSED	
			M	SD	M	SD	M	SD	M	SD
			73.3	1.56	74.91	1.32	75.58	1.30	75.78	1.29
BL_NoSED	M	73.3			t(358) = -10.6 P=0.00 ✓		t(358)= -15.08 P=0.00 ✓		t(358): -14.232 P=0.00 ✓	
	SD	1.56								
S1_NoSED	M	74.91					t(358) = -4.815 P=0.00 ✓		t(358) = -6.27 P=0.00 ✓	
	SD	1.32								
S2_NoSED	M	75.58							t(358) = -1.449 P=0.148 ×	
	SD	1.30								
S3_NoSED	M	75.78								
	SD	1.29								

M: Mean; SD: Standard deviation; ×: Insignificant difference; ✓: Significant difference

Table S3. t-test for the reliability when sedimentation was included over 10-year simulations.

Independent sample t-test Reliability (%) Sedimentation included			BL_SED		S1_SED		S2_SED		S3_SED	
			M	SD	M	SD	M	SD	M	SD
			73.16	1.49	74.6	1.32	75.3	1.32	75.2	1.29
BL_SED	M	73.16			t(358)= -9.90 P=0.00 ✓		t(358)= -14.45 P=0.00 ✓		t(358)= -13.81 P=0.00 ✓	
	SD	1.49								
S1_SED	M	74.6					t(358)= -4.84 P=0.00 ✓		t(358)= -4.07 P=0.00 ✓	
	SD	1.32								
S2_SED	M	75.3							t(358)= 0.809 P=0.42 ×	
	SD	1.32								
S3_SED	M	75.2								
	SD	1.29								

Table S4. t-test for the reservoir reliability between scenarios with and without sedimentation over 10-year simulations.

Independent sample t-test Reliability (%)	BL_SED		S1_SED		S2_SED		S3_SED	
	M	SD	M	SD	M	SD	M	SD

Sedimentation included			73.16	1.49	74.6	1.32	75.3	1.32	75.2	1.29
BL_NoSED	**M**	73.3	t(358)= 0.85 P=0.40 ×							
	SD	1.56								
S1_ NoSED	**M**	74.91			t(358)= 1.98 P=0.05 ✓					
	SD	1.32								
S2_ NoSED	**M**	75.58					t(358)= 1.96 P=0.05 ✓			
	SD	1.30								
S3_ NoSED	**M**	75.78							t(358)= 4.26 P=0.00 ✓	
	SD	1.29								

Table S5. t-test for the water releases when sedimentation was not included over 10-year simulations.

Independent sample t-test Water releases (Mcm) Sedimentation not included			BL_NoSED		S1_NoSED		S2_NoSED		S3_NoSED	
			M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
			3903.5	78.06	3989.4	66.5	4024.9	65.2	4035.4	64.4
BL_NoSED	**M**	3903.5			t(358) = -11.23 P=0.00 ✓		t(358)= -16.01 P=0.00 ✓		t(358): -17.48 P=0.00 ✓	
	SD	78.06								
S1_NoSED	**M**	3989.4					t(358)= -5.12 P=0.00 ✓		t(358)= -6.67 P=0.00 ✓	
	SD	66.5								
S2_NoSED	**M**	4024.9							t(358)= -1.54 P = 0.125 ×	
	SD	65.2								
S3_NoSED	**M**	4035.4								
	SD	64.4								

Table S6. t-test for the water releases when sedimentation was included over 10-year simulations.

Independent sample t-test Water releases (Mcm) Sedimentation included			BL_SED		S1_SED		S2_SED		S3_SED	
			M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
			3896.3	75.16	3974.7	66.59	4010.5	3896.28	4004.58	65.48
BL_SED	**M**	3896.3			t(358)= -10.48 P=0.00 ✓		t(358)= -15.3 P=0.00 ✓		t(358)= -14.58 P=0.00 ✓	
	SD	75.16								
S1_SED	**M**	3974.7					t(358)= -5.12 P=0.00 ✓		t(358)= -4.29 P=0.00 ✓	
	SD	66.59								
S2_SED	**M**	4010.5							t(358)= 0.86 P=0.39 ×	
	SD	3896.28								
S3_SED	**M**	4004.58								
	SD	65.48								

Table S7. t-test for the water releases between scenarios with and without sedimentation over 10-year simulations.

Independent sample t-test Water releases (Mcm) Sedimentation included	BL_SED		S1_SED		S2_SED		S3_SED	
	M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
	3896.3	75.16	3974.7	66.59	4010.5	3896.28	4004.58	65.48

BL_NoSED	**M**	3903.5	t(358)= 0.90 P=0.37 ×			
	SD	78.06				
S1_NoSED	**M**	3989.4		t(358)= 2.10 P=0.04 ✓		
	SD	66.5				
S2_NoSED	**M**	4024.9			t(358)= 2.08 P=0.04 ✓	
	SD	65.2				
S3_NoSED	**M**	4035.4				t(358)= 4.51 P=0.00 ✓
	SD	64.4				

Table S8. t-test for the water spillage when sedimentation was not included over 10-year simulations.

Independent sample t-test Water spillage (Mcm) Sedimentation not included			**BL_NoSED**		**S1_NoSED**		**S2_NoSED**		**S3_NoSED**	
			M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
			663.63	62.37	722.37	60.73	754.75	62.49	763.56	62.35
BL_NoSED	**M**	663.63			t(358) = -9.05 P=0.00 ✓		t(358) = -13.84 P=0.00 ✓		t(358) = -15.20 P=0.00 ✓	
	SD	62.37								
S1_NoSED	**M**	722.37					t(358) = -4.98 P=0.00 ✓		t(358) = -6.35 P=0.00 ✓	
	SD	60.73								
S2_NoSED	**M**	754.75							t(358) = -1.34 P=0.18 ×	
	SD	62.49								
S3_NoSED	**M**	763.56								
	SD	62.35								

Table S9. t-test for the water releases when sedimentation was included over 10-year simulations.

Independent sample t-test Water spillage (Mcm) Sedimentation included			**BL_SED**		**S1_SED**		**S2_SED**		**S3_SED**	
			M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
			677.69	63.69	738.33	61.56	776.47	62.28	809.13	64.54
BL_SED	**M**	677.69			t(358)= -9.18 P=0.00 ✓		t(358)= -14.88 P=0.00 ✓		t(358)= -19.45 P=0.00 ✓	
	SD	63.69								
S1_SED	**M**	738.33					t(358)= -5.84 P=0.00 ✓		t(358)= -10.65 P=0.00 ✓	
	SD	61.56								
S2_SED	**M**	776.47							t(358)= -4.88 P=0.00 ✓	
	SD	62.28								
S3_SED	**M**	809.13								
	SD	64.54								

Table S10. t-test for the water spillage between scenarios with and without sedimentation over 10-year simulations.

Independent sample t-test Water spillage (Mcm) Sedimentation included	**BL_SED**		**S1_SED**		**S2_SED**		**S3_SED**	
	M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
	677.69	63.69	738.33	61.56	776.47	62.28	809.13	64.54

BL_NoSED	**M**	663.63	t(358)= -2.12 P=0.03 ✓			
	SD	62.37				
S1_NoSED	**M**	722.37		t(358)= -2.48 P=0.01 ✓		
	SD	60.73				
S2_NoSED	**M**	754.75			t(358)= -3.30 P=0.00 ✓	
	SD	62.49				
S3_NoSED	**M**	763.56				t(358)= -6.81 P=0.00 ✓
	SD	62.35				

Table S11. t-test for the reliability, water releases and water spillage when sedimentation was and was not included over 40-year simulations.

Reservoir indicators	M	SD	t	p-value	Statistically difference
Reliability (%)					
S3_noSED	76.04	0.69	28.1	0.00	✓
S3_SED	73.4	0.63			
Water releases (Mcm)					
S3_noSED	16199	144.5	28.17	0.00	✓
S3_SED	15639	136.7			
Water spillage (Mcm)					
S3_noSED	3039	166.1	-27.7	0.00	✓
S3_SED	3700	170.3			

Table S12. t-test for the reliability, water releases and water spillage when sedimentation was included over 40-year simulations.

Reservoir indicators	M	SD	t	p-value	Statistically difference
Reliability (%)					
S3_SED_40yr	73.4	0.63	17.23	0.00	✓
S3_SED_10yr	75.79	1.22			
Water releases (Mcm/year)					
S3_SED_40yr	390.98	3.41	12.39	0.00	✓
S3_SED_10yr	400.37	6.77			
Water spillage (Mcm/year)					
S3_SED_40yr	92.51	4.26	-15.491	0.00	✓
S3_SED_10yr	80.99	6.09			

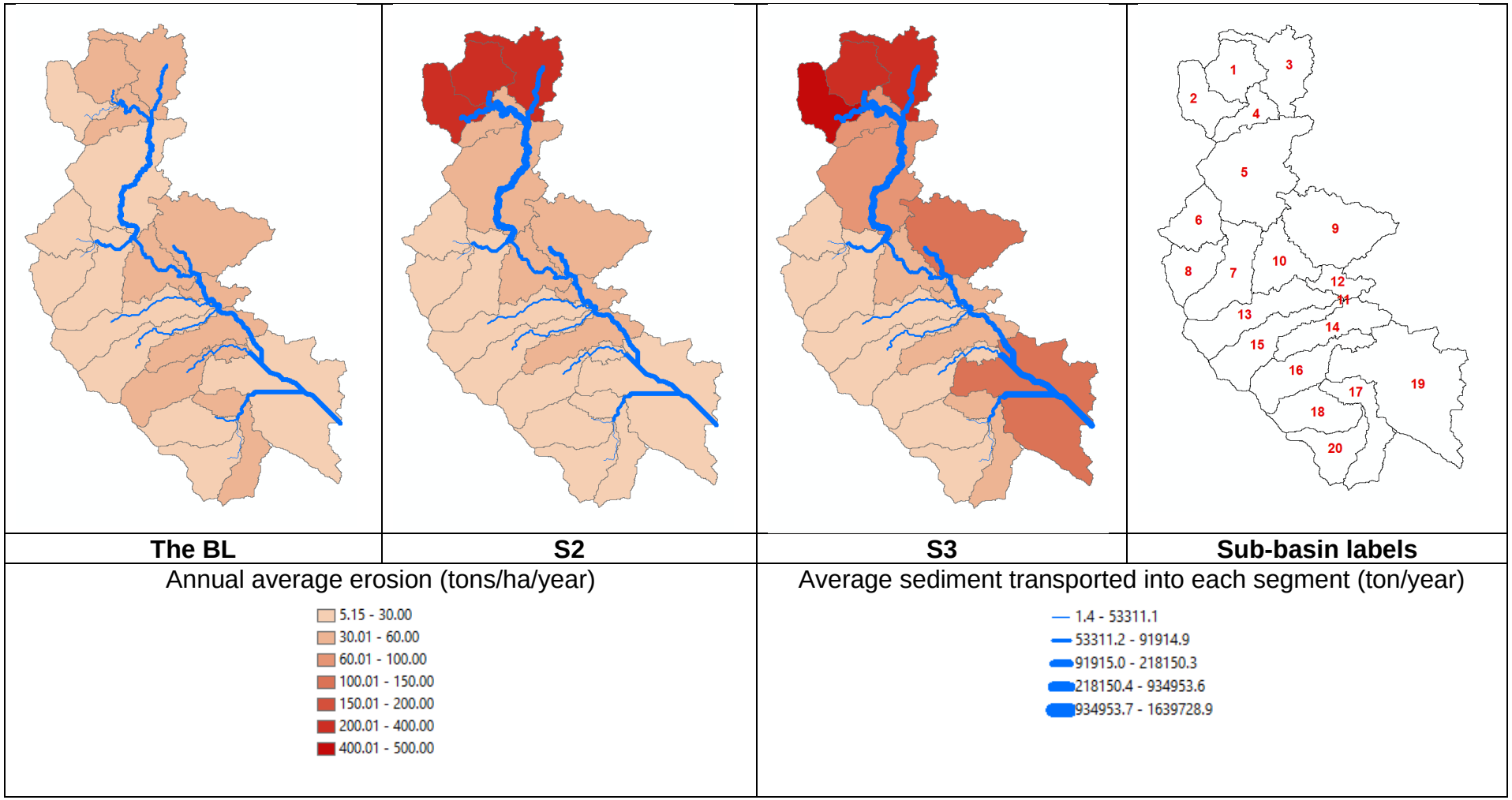


Figure S2. The median values of water and sediment flows in the sub-basins of the case study

Table S13. Growth phases of crops

No.	Parameters	Description	FRSE (Forest)		ORCD (Tea tree)		RICE (Paddy)		AGRR (Annual vegetable)		RNGB (Range Bush)	
			Default value	Modified value	Default value	Modified value	Default value	Modified value	Default value	Modified value	Default value	Modified value
1	BLAI	Maximum potential leaf area index (m^2/m^2)	5	5	4	2.5	5	3	3	3	2	2
2	FRGRW1	Fraction of the plant growing season corresponding to the 1st point on the optimal leaf area development curve	0.15	0.15	0.1	0.03	0.3	0.3	0.15	0.15	0.05	0.05
3	LAIMX1	Fraction of BLAI corresponding to the 1st point on the optimal leaf area development curve	0.7	0.7	0.15	0.15	0.01	0.01	0.05	0.05	0.1	0.1
4	FRGRW2	Fraction of the plant growing season corresponding to the 2nd point on the optimal leaf area development curve	0.25	0.25	0.5	0.14	0.7	0.7	0.5	0.5	0.25	0.25
5	LAIMX2	Fraction of BLAI corresponding to the 2nd point on the optimal leaf area development curve	0.99	0.99	0.75	0.75	0.95	0.95	0.95	0.95	0.7	0.7
6	DLAI	Fraction of growing season when leaf area begins to decline	0.99	0.99	0.99	0.83	0.8	0.8	0.7	0.7	0.35	0.35
7	CHTMX	Max canopy height (m)	10	6	3.5	1.2	0.8	0.8	2.5	1	1	0.5
8	Year to maturity	Years for plants to reach maturity	30	30	10	5	0	0	0	0	0	0
9	Others			Default		Default		Default		Default		Default
Related to sediment												
1	USLE_C		0.001	0.005	0.001	0.073	0.03	0.02	0.2	0.2	0.003	0.002
2	Spcon		0.0001	0.0005	0.0001	0.0005	0.0001	0.0005	0.0001	0.0005	0.0001	0.0005

Appendix B

Table S14. Historical data of water demands.

Month	Agriculture			Urban use			Downstream river		
	Min	Median	Max	Min	Median	Max	Min	Median	Max
Jan	22.1	37.3	43.9	6.4	7.1	7.9	0.0	0.0	0.0
Feb	22.0	34.4	44.5	6.4	7.1	7.9	0.0	6.2	9.4
Mar	34.7	43.5	48.4	6.4	7.1	7.9	0.0	4.8	11.7
Apr	20.9	33.6	39.0	6.4	7.1	7.9	0.0	3.2	10.8
May	12.7	28.8	35.8	6.4	7.1	7.9	0.0	2.0	6.9
Jun	18.7	29.5	36.3	6.4	7.1	7.9	0.0	0.0	0.0
Jul	25.8	35.1	42.8	6.4	7.1	7.9	0.0	0.0	0.0
Aug	34.4	41.1	44.5	6.4	7.1	7.9	0.0	0.0	0.0
Sep	23.0	44.4	58.5	6.4	7.1	7.9	0.0	0.0	0.0
Oct	11.4	38.5	60.7	6.4	7.1	7.9	0.0	0.0	0.0
Nov	17.2	28.0	37.4	6.4	7.1	7.9	0.0	0.0	0.0
Dec	28.5	43.2	50.3	6.4	7.1	7.9	0.0	0.0	0.0

Table S15 . Comparison in RRV and water spillage between the baseline and each scenario

No	Scenarios	Reliability Range (Min-Max)	Median Reliability (%)	Resilience Range (Min-Max)	Median Resilience (%)	Vulnerability Range (Min-Max)	Median Vulnera -bility	Median Spillage (Mcm/yr)
1	Baseline	67.9-76.7	73.2	30.4-73.3	52.2	5.9-10.9	7.9	67.4
2	Change in water demand – Option A *(Table 4.2)*							
	LU-S1 and CCSM-M	60.9-66.5	63.8	17.7-42.3	28.6	8.7-11.7	10.17	134.3
	LU-S1 and GFDL-M	65-70.9	67.9	24-51.3	35.6	7.9-11.1	9.56	176.8
	LU-S1 and CCSM-H	60.6-66.5	63.6	18.8-38.2	28.8	8.5-11.4	10.05	204.1
	LU-S1 and GFDL-H	68.4-74.9	71.5	23.4-52.9	37.5	7.6-11.5	9.31	314.1
	LU-S2 and CCSM-M	57.2-62.6	59.9	14.5-28.8	19.1	9.9-13.5	11.68	165.5
	LU-S2 and GFDL-M	60.7-66.6	63.6	16.9-32.7	23.2	10.1-13.6	11.47	210.8
	LU-S2 and CCSM-H	–	–	–	–	–	–	–
	LU-S2 and GFDL-H	–	–	–	–	–	–	–
3	*Apply the best management practices for agricultural areas – Option B (Table 4.2)*							
	LU-S1 and CCSM-M	61.4-66.8	64.1	19.3-42.3	29.6	8.0-11.4	10.2	131.7
	LU-S1 and GFDL-M	65.3-71.2	68.2	25.0-51.3	37.2	7.5-11.0	9.4	173.9
	LU-S1 and CCSM-H	61.3-66.9	64.0	19.0-40.0	29.3	8.6-11.6	9.9	201.1
	LU-S1 and GFDL-H	68.8-75.4	72.0	26.1-57.6	40.0	7.4-11.8	9.1	310.2
	LU-S2 and CCSM-M	60.1-65.5	62.6	15.3-37.3	25.8	9.1-12.1	10.4	144.8
	LU-S2 and GFDL-M	63.7-69.5	66.6	20.7-48.8	32.7	8.4-12.0	10.1	188.1
	LU-S2 and CCSM-H	59.8-65.0	62.2	15.9-34.0	24.2	8.8-11.8	10.4	216.7
	LU-S2 and GFDL-H	66.6-72.8	69.4	23.4-45.2	32.6	8.7-11.8	10.1	331.0
4	*Reduction in minimum requirement of water level for tourism – Option C (Table 4.2)*							
	LU-S1 and CCSM-M	63.7-69	66.4	26.4-50	36.54	7.7-11.5	9.67	120.4
	LU-S1 and GFDL-M	67.4-73.3	70.4	27.7-61.8	43.18	6.8-10.5	8.73	164.1
	LU-S1 and CCSM-H	64.1-69	66.3	23.2-48.1	34.65	7.8-11.2	9.48	189.5
	LU-S1 and GFDL-H	70.4-76.8	73.7	30.8-64.5	47.22	6.3-10.4	8.32	303.1
	LU-S2 and CCSM-M	60-65.2	62.6	14.5-33.9	23.54	9.2-11.7	10.45	150.9
	LU-S2 and GFDL-M	63.1-69	66.0	20-39.1	28.57	8.6-12.4	10.17	198.7
	LU-S2 and CCSM-H	59.6-64.4	61.8	14.7-31	21.31	9-12.3	10.70	226.0
	LU-S2 and GFDL-H	64.1-70.1	67.1	17.9-34.9	22.64	9.8-13	11.45	354.2
5	*Reduction in water demand for agriculture and minimum requirement of water level for tourism – Option D (Table 4.2)*							
	LU-S1 and CCSM-M	72-77.9	74.79	35.3-71.4	50.0	4.8-8.7	6.47	163.8

No	Scenarios	Reliability Range (Min-Max)	Median Reliability (%)	Resilience Range (Min-Max)	Median Resilience (%)	Vulnerability Range (Min-Max)	Median Vulnera -bility	Median Spillage (Mcm/yr)
	LU-S1 and GFDL-M	75.4-82.2	78.94	41.4-83.3	61.7	4.6-8.1	6.05	211.6
	LU-S1 and CCSM-H	72-78.3	74.85	30-72	46.9	4.5-8.2	6.15	234.3
	LU-S1 and GFDL-H	79.1-85.6	82.21	34.8-100	65.9	4.2-8.1	5.74	354.9
	LU-S2 and CCSM-M	67.1-72.9	69.78	21.4-54.1	38.3	5.6-8.2	6.92	195.6
	LU-S2 and GFDL-M	70-76.7	73.36	26.3-61.3	43.9	5.7-8.4	6.96	246.5
	LU-S2 and CCSM-H	66.2-72.3	69.12	24.5-48.8	34.7	5.8-9.2	7.22	270.8
	LU-S2 and GFDL-H	70.4-77	73.50	20.8-52.8	34.1	6.6-9.4	7.71	408.4
6	*Change minimum sector demand priorities – Option E (Table 4.2)*							
	LU-S1 and CCSM-M	61.1-66.6	63.73	11.5-21.1	15.28	16.5-20.6	18.19	134.6
	LU-S1 and GFDL-M	65-70.9	67.86	12.5-26.6	18.46	14.5-19.4	16.90	176.5
	LU-S1 and CCSM-H	60.9-66.5	63.64	11.7-22.7	15.49	16.5-20.2	18.15	204.1
	LU-S1 and GFDL-H	68.4-74.9	71.47	15.9-32.7	21.67	14.8-19	16.49	314.1
	LU-S2 and CCSM-M	57.2-62.6	59.88	11.5-17.1	12.99	19.2-22.9	20.87	165.7
	LU-S2 and GFDL-M	60.6-66.6	63.64	12.2-21.2	15.94	17.8-21.9	20.07	211.1
	LU-S2 and CCSM-H	–	–	–	–	–	–	–
	LU-S2 and GFDL-H	–	–	–	–	–	–	–

Appendix C

Determining the Reliability, Resilience and Vulnerability based on indicators define in Ehteram et al. (2018); Ghimire et al. (2014); Hashimoto et al. (1982); Loucks et al. (2017)

S_t is an indicator of whether the reservoir system is in a satisfactory (constraints satisfied) or unsatisfactory state. In this study, the system is said to be in satisfactory condition if the water supply meets the constraints and exceeds the minimum allowed releases (MR_t) in Equation (4.1), otherwise the system is in unsatisfactory state and the indicator, St, is equal to zero.

The indicator, S_t, is mathematically defined by the equation below (Ghimire et al., 2014):

$$S_t = \begin{cases} 1 & if\ R_t \geq \mathrm{MR}_t \\ 0 & Else \end{cases}, \qquad \forall t$$

Where, MR_t is minimum allowable releases.

An index, C_t, is mathematically defined in the following equation to identify the system transition from an unsatisfactory to satisfactory condition (Ghimire et al., 2014):

$$C_t = \begin{cases} 1 & if\ R_t < \mathrm{MR}_t\ \ and\ R_{t+1} \geq \mathrm{MR}_t \\ 0 & otherwise \end{cases}, \qquad \forall t$$

1.1. Reliability

$$\propto = \frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} D_t} \times 100\%$$

Where α is the reservoir reliability (%). A higher percentage for this index shows the demands are well supplied based on released water; R_t is the volume of water released and D_t is the volume of water demanded in the operational period T.

1.2. Resilience

$$\beta = \frac{\sum_{t=1}^{T} C_t}{T - \sum_{t=1}^{T} S_t} \times 100\% \,, \qquad \forall t$$

Where β is the resilience (%). When the system has a higher resilience index, it can fast recover from an unsatisfactory condition; T is the total number of months in the operational period T.

1.3. Vulnerability

$$\gamma = \frac{\sum D_t}{T - \sum_{t=1}^{T} S_t} \,, \qquad \forall t$$

Where γ is the vulnerability (-). A low vulnerability shows a low intensity of failure occurrences in the system based on the difference between released water and demands; D_t is the deficit or extent of failure during time period t, which is determined by D_t = Max ($MR_t - R_t$,0).