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A Framework to Assess the Reliability of a Multipurpose Reservoir under Uncertainty in Land Use

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Abstract: Socioeconomic development in watersheds lead to land-use changes, which can alter water and sediment inflows into reservoirs, leading to uncertainty in water supply reliability. A modelling framework coupling the Soil and Water Assessments Tool (SWAT) and the @RISK genetic algorithm optimisation tool was developed to optimise water allocation and estimate water supply reliability under uncertainty in future land-use. The multi-purpose Nuicoc reservoir in Vietnam was used as a case study. Modelling results showed that an expansion of the urban areas by 10% and conversion of 5% of the forest to agricultural areas produced the highest water releases for downstream demands of all simulated scenarios, with 5 Mcm/year greater water releases than the baseline for the case where sedimentation was not considered. However, when sedimentation was considered, it generated the greatest decrease in water releases, with 6.25 Mcm/year less than the baseline. Additionally, it was determined that spatial distribution of land-use significantly affect sediment inflows into the reservoir, highlighting the importance of targeted sediment management. This demonstrates the usefulness of the proposed framework for decision-makers in assessing the impact of possible land-use changes on the reservoir operation.

Keywords: reservoir operations; water reliability; genetic algorithm; land-use change; sedimentation

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1. Introduction

Available freshwater resources in rapidly developing countries are becoming scarce due to higher demands from industrial, recreational, municipal, and agricultural sectors [1,2]. In addition, socioeconomic developments can lead to significant changes in land-use, which can subsequently impact on water resources critical for downstream economic development [3]. 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 [3,4].

Reservoirs are widely used to manage water resource storage and allocation for multiple water demands [5]. 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 [3,6]. Changes in forest, urban and agricultural land-use areas in a reservoir watersheds can thus cause changes in the way water in a reservoir is managed [3,7]. 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 [8–10]. 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 [3,11,12]. 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, 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 [3]. 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 [11]. 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 [12]. 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 a significant increase in streamflow, whereas groundwater contribution to streamflow decreased due to decreasing urban infiltration [2].

The optimisation of water supply from reservoirs to meet demand is also an area of intensive research i.e., [1,7,13–17]. Genetic optimisation algorithms (GAs) 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” [18]. GAs can solve large-scale, nonlinear problems with a large number of variables, and have the capacity of finding global solutions [19–21]. 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., [7,15,17,22]. 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 this uncertainty [23]. For example, an approach called the probabilistic multiple objective genetic algorithm [24] was used to incorporate uncertainty into 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) [25]. 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 [25].

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 [26]. 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 [7]. 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 socioeconomic development scenarios. Similarly, Anand et al. [15] 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 this 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 socioeconomic-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.

2. Materials and Methods

2.1. The Framework

SWAT and the @RISK genetic optimisation tool [27] were incorporated in a framework to determine reservoir water supply reliability under uncertainty (Figure 1). SWAT is used widely for river hydrology, but it does not have a capability to determine optimal water allocation for downstream water users [28]. On the other hand, @RISK is a widely used tool for optimisation under uncertainty [25], 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, probability distributions are computed.

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 1. A framework to assess the impact of land-use change on reservoir water supply reliability.

Uncertainty in water demand is also considered. During the operational period of a reservoir, monthly water demand 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 [29] is then used to randomly create a number of possible combinations of water inflows, 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 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.

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 [30]. The second phase determines the routing of water and sediment through the channel network of the watershed to the outlet [30]. Manning's equation is applied to define the rate and velocity of flow in a channel segment. Water is routed through the open channel network using the variable storage routing method. 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 [31]. 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 [30].

SWAT-CUP (SWAT Calibration and Uncertainty Programs) is a standalone program developed for calibration of SWAT [32]. In this research, for model calibration and valida-

tion and for the determination of uncertainties, we used the program SUFI-2 (Sequential Uncertainty Fitting Algorithm—Version 2) in SWAT-CUP [32,33]. 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 climate or/and 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 [34]. 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) [34] (Figure 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 [35] 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 [36], 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 [32].

Figure 2. Obtaining the 95% probability distribution (95PPU) using SWAT-CUP to quantify parameter uncertainty [37].

2.1.2. Optimisation Tool

To maximise the 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 [23,25].

Genetic Algorithms (GA), developed by Holland [38], 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., [14–17,39]. 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 [40]. 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 (1)), (ii) Decision variables (water releases), and (iii) Constraints (Equations (2)–(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 maximise total reservoir release for each sector demand (i.e., urban, agriculture, etc.) over an operational period. The objective is described by Equation (1) (Minimize sum of squared deviation between demands and supplies).

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

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:

$$S_{i,j+1} = S_{i,j} + I_{i,j} - E_{i,j} - R_{i,j} - O_{i,j} \quad (2)$$

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 ($S_{\max}$)

$$\begin{cases} S_{i,j} \leq S_{\max} \\ S_{i,j} \geq S_{\min} \end{cases} \quad (3)$$

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,

$$S_{i,5} \geq 55 \text{ Mcm} \quad (4)$$

(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 Ziaei et al. [1], Goodarzi et al. [4]):

$$U_{i,j} + aA_{i,j} + bD_{i,j} \leq R_{i,j} \leq U_{i,j} + A_{i,j} + D_{i,j} \quad (5)$$

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 problem of potential ongoing water shortages for agriculture will be solved by finding other available water sources or considering changing 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)

$$P_1 = \max \begin{cases} 0 & \text{if } S_{i,j+1} < S_{\max} \\ \sum \sum (S_{i,j+1} - S_{\max})^2 & \text{if } S_{i,j+1} > S_{\max} \end{cases} \quad (6)$$

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

$$P_2 = \max \begin{cases} 0 & \text{if } R_{i,j} > U_{i,j} + aA_{i,j} + bD_{i,j} \\ \sum \sum ([U_{i,j} + aA_{i,j} + bD_{i,j}] - R_{i,j})^2 & \text{if } R_{i,j} < U_{i,j} + aA_{i,j} + bD_{i,j} \end{cases} \quad (7)$$

If the reservoir storage and water release do not satisfy the constraints (Equations (3) and (4)), the penalty function defined in Equations (6) and (7) are added to the objective function (Equation (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. [28] 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.

2.1.3. Model Performance Indicators

Performance indicators are essential to assess operation periods of water resource systems [41]. The water supply reliability indicator was considered in this study. According to Hashimoto et al. [41], water supply reliability is the probability that the reservoir operates in the set of satisfactory states. The volume reliability in water supply (Equation (8)) was used by Jain and Bhunya [42] and Ehteram et al. [13] 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.

$$R_{ev} = \frac{V_s}{V_d} \times 100 (\%) \quad (8)$$

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 [42].

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.

2.2. Nuicoc Watershed Case Study

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). The average annual rainfall and evaporation in the 575-km² watershed are estimated at 1850 mm and 1100 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.

Figure 3. Location of the Nuicoc reservoir and watershed in the Thai Nguyen province of Vietnam.

Forests account for 52% of the area, crop cultivation for 30%, rural residential areas 9%, urban residential areas 1.2%, and other land account for the remaining 7.8%. Considerable socioeconomic 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 2460 ha. It was designed to supply water for agriculture (irrigation), urban supply, tourism, and to maintain required flows for a downstream river nearby.

2.2.2. Data Sources and Pre-Processing for the Case Study

Input data for SWAT were collected from different sources (Table 1). The Digital Elevation Model (DEM) at $30\text{ m} \times 30\text{ m}$ resolution was extracted from The Shuttle Radar Topography Mission (SRTM) database [43]. Land use, land cover (LULC) maps of 2004 and 2014 were provided by the Thainguyn 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 [44]. 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 was taken from Climate Forecast System Reanalysis (CFSR) [45]. The growth phases of crops were obtained from local data (Supplementary Materials Table S13).

Table 1. Input data for the SWAT.

Data	Duration	Source	Collection Month
Digital Elevation Model (DEM) (30 m × 30 m)		The Shuttle Radar Topography Mission database [43]	
Land-use	2004, 2014	Thainguyen Department of Resources and Environment, 2018	2/2018
Soil map and properties		FAO [44]	
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 [45]	
Growth phases of crops		Handbook of plantings [46]	

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 [47] 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 [47]. 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. The reservoir capacity to annual inflow is approximately 0.5, resulting in a very high potential trapping efficiency [48]. For simplicity, this study assumed that 100% of sediment inflow was trapped in the reservoir.

2.2.3. Case Study Calibration and Validation

The following steps were followed to calibrate and validate the SWAT model for the case study [34,49]:

Step 1: The SWAT model was setup using input data summarised in Table 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 [50].

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. [50]. The SUFI2 module was used. For our case study, while there was a good match for the seasonal streamflow dynamics, there was less agreement for peak flows. We determined that 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

the most sensitive to the peak rate of streamflow. 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 [34]. 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 [34]. 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 [34]. Each iteration needs at least 200 simulations to consider possible parameter combinations [32]. 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 ET obtained from SWAT-CUP was compared with the ET generated by the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite at a resolution of 500 m 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.

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 socioeconomic 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) [51] 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 [3]. 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 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.

Figure 4. Percentage of each land-use in the baseline and land-use change scenarios (a); BL and projected scenarios of LULC change (b).

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 assumed that monthly inflows to the reservoir are independent and uniformly distributed within an area bounded by the lower values and upper values of 95PPU. The combination of the random monthly inflows over the simulation period creates a unique inflow time series that was 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 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. To quantify the uncertainty of water inflow in simulations, a uniform distribution was applied for each month to generate monthly water inflows randomly. However, this approach cannot be used for sediment inflows as it depends on water inflows. It is therefore assumed that the relation between water inflows and sediment inflows 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 years of operation, from 1982; and that, the inclusion of sediment will not affect the reservoir surface.

Figure 5. Historical water demand distributions from agriculture (a), urban use (b) and downstream river (c).

3. Results

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 6, Table 2). This satisfied the goodness-of-fit range proposed by Abbaspour [34]. In addition, as suggested by ASABE [36], the best simulation provided very good values of NS and PBIAS, which are 0.85 and 2.37%, respectively (Table 2).

Table 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 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 [30,52]. 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 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.**Figure 7.** Cont.

(b) AET of SWAT and MODIS

Figure 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 8), equal to historical average measurements for the period from 1976 to 2001 (0.5 Mcm/year) [47].

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). While S3 has the highest average water inflows (16.12 m³/s), especially in wet seasons (27.3 m³/s), followed by S2 (16.07 m³/s), their dry water inflows are the lowest, at 4.93 m³/s and 4.95 m³/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 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).

Table 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 8. Sediment inflows into the reservoir using the baseline land-use map.

Figure 9. Transition from forest to agricultural areas surrounding the reservoir, under S2 (a) and S3 (b).

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 10).

Independent sample *t*-tests were conducted to compare performance indicators of the baseline with those of each scenario simulated using the probabilistic approach (Tables 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 10a–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.

Figure 10. Impact of land-use changes on the reliability (a), water release (b), and water spillage (c) 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 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 10). The trend in the median of the performance indicators for the probabilistic approach is the 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 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 11a,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 11c). 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.

Figure 11. Assessing the reliability (a), water release (b), and water spillage (c) 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 12, Table 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 h. 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 h than the latter, and the median and mean reliabilities achieved by these two these n -values are the same (Table 4).

Table 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 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.

Figure 12. Water supply reliability (a), water release (b) and water spillage (c) 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).

4. Discussion

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 [25]. 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 [29,53]. 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 4). Lastly, it is also noted that the range of reliability over 40 years was narrower than that over 10 years (Figure 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 [34]. 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.

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 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 [3,11], 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 [54,55].

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.

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 and Figure 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 [56] or other regions [57], should be emphasised in the planning and managing of land-use.

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.

Supplementary Materials: The following are available online at <https://www.mdpi.com/2073-4441/13/3/287/s1>, Figure S1: Time series of the reservoir over the 10-year period, Figure S2: The median values of water and sediment flows in the sub-basins of the case study, Table S1: List of calibrated ranges of parameters, Table S2: *t*-test for the reliability when sedimentation was not included over 10-year simulations, Table S3: *t*-test for the reliability when sedimentation was included over 10-year simulations, Table S4: *t*-test for the reservoir reliability between scenarios with and without sedimentation over 10-year simulations, Table S5: *t*-test for the water releases when sedimentation was not included over 10-year simulations, Table S6: *t*-test for the water releases when sedimentation was included over 10-year simulations, Table S7: *t*-test for the water releases between scenarios with and without sedimentation over 10-year simulations, Table S8: *t*-test for the water spillage when sedimentation was not included over 10-year simulations, Table S9: *t*-test for the water releases when sedimentation was included over 10-year simulations, Table S10: *t*-test for the water spillage between scenarios with and without sedimentation over 10-year simulations, Table S11: *t*-test for the reliability, water releases and water spillage when sedimentation was and was not included over 40-year simulations, Table S12: *t*-test for the reliability, water releases and water spillage when sedimentation was included over 40-year simulations, Table S13: Growth phases of crops.

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