Estimating Reservoir Inflow and Outflow From Water Level Observations Using Expert Knowledge: Dealing With an Ill-Posed Water Balance Equation in Reservoir Management

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Abstract  Quantifying reservoir water balance is an essential process for the efficient management of water resources. Water level records are often the only data available for reservoir analysis, which causes an ill-posed problem in water resource system planning. This study proposes an analytical framework to estimate reservoir inflow and outflow from water level observations using hydrological models and reasoning carefully derived from expert knowledge and soft data. Partial reservoir inflow hydrographs were constructed from water level observations using a continuity equation and knowledge-based constraints developed for periods of no spillway discharge. A bucket-type rainfall-runoff model was then calibrated to the partial inflow hydrographs. Finally, a complete reservoir inflow hydrograph was constructed using the calibrated models, which were then employed to estimate detailed reservoir outflow components under a full water balance relationship between inflow, outflow, water levels, and reservoir operation rules. The proposed solution for the ill-posed water balance equation outperformed conventional (benchmark) approaches in accuracy and uncertainty in its application to agricultural reservoirs. This study demonstrates how hydrological modeling and reasoning, which are discreetly designed based on expert knowledge, can help to solve the ill-posed water balance equation by creating supplementary information regarding the problem. The proposed framework is expected to assist in reconstructing reservoir routing processes using water level observations for hydrological analysis and water resource management planning.

1. Introduction

A reservoir is used to manage water resources, and its inflow and outflow hydrographs are critical to reservoir planning for agricultural, industrial, and municipal water uses; hydropower production; recreation; ecological requirements; and flood protection (Ehsani et al., 2017; Gragne et al., 2015; Habets et al., 2018; Jiang et al., 2019; Yang et al., 2017). A reservoir water budget is associated with many different hydrological processes, such as direct deposit of rainfall, surface evaporation, drainage from upstream areas (inflow), and water release through spillways (outflow). However, weather data and reservoir water levels are often the only observations available for a water budget analysis (Deng, Liu, Liu, et al., 2015; Kummel, et al., 2014; Zhou et al., 2019). Even when there are streamflow records that can be used to estimate the rates of inflow to a reservoir, they are usually limited to the main streams, and data on discharge from tributaries are rare (Can & Houck, 1984; Deng, Liu, Guo, et al., 2015; Zhou et al., 2019). Thus, the reservoir budget is usually estimated on the basis of reservoir water balance, but it can become an ill-posed problem due to the lack of observations.

The ill-posed water balance equation can be resolved only when two of the three terms or variables—namely inflow, water level, and outflow—become known. Thus, when reservoir water level records are available, the water balance equation can be solved by estimating one of the two remaining unknown variables of inflow and outflow. Previous studies (using conventional methods) have estimated the inflow or outflow of ungauged reservoirs using regionalized rainfall-runoff models (for inflow; e.g., Kang & Park (2014); Song et al. (2016); Yokoo et al. (2001)) or regionalized reservoir operation models (for outflow; e.g., Hanasaki et al., 2006; Yassin et al., 2019) that do not require calibration processes with direct observations. Then, the conventional approaches predict the remaining unknown from the predetermined estimates and mass balance relationships. However, inflow or outflow approximation from regionalized modeling is subject to error and uncertainty (Arsenault et al., 2019; Parajka et al., 2013) because the statistical relationship between parameter values and landscape...
characteristics tends to have outliers that cannot be explained by the regression lines. Given that regionalization processes are commonly implemented on large spatial scales, the application of regionalized models to local agricultural reservoirs is prone to inaccuracy.

When inflow and outflow records are not available to solve water balance equations, reservoir water level records can provide the information required to estimate the inflow and outflow if the records are carefully classified based on expert knowledge. The application of expert knowledge and supplementary information has been successful in solving hydrological inverse problems. For example, model parameter values are commonly constrained based on the understanding of the physical basis of the parameters and model structure (hydrological reasoning; e.g., Gharari et al., 2021; Gharari, Hrachowitz, et al., 2014; Gharari, Shafiei, et al., 2014; Hrachowitz et al., 2014) and/or information derived from indirect observations (often referred to as soft data; e.g., Jan Seibert & McDonnell, 2002; Nijzink et al., 2018). A reservoir rule curve can provide information that can be used to constrain the parameter space of watershed and reservoir routing modeling (for inflow and outflow estimation), thereby increasing accuracy and reducing uncertainty (or equifinality) in a reservoir water balance analysis. However, expert knowledge has not been commonly employed to solve the ill-posed reservoir water balance problem.

This study proposes a framework to estimate reservoir inflow and outflow from water level observations using expert knowledge. In this framework, hydrological periods are carefully separated into segments based on the understanding of reservoir operation and water balance to relax the ill-posed equation and create partial inflow hydrographs required to calibrate a hydrological model for the entire period. Then, reservoir outflow is quantified through reservoir water balance analysis enhanced by information from a reservoir rule curve analysis. This study demonstrates how expert knowledge and hydrological reasoning can help to solve an ill-posed reservoir balance problem with a limited number of reservoir observations. This article also describes the applicability and limitations of the proposed framework and discusses the implications of the findings.

2. Methods

2.1. Overall

This study presents a framework to resolve the ill-posed reservoir water balance problem using expert knowledge and hydrological reasoning (Figure 1). The framework identifies periods that have zero reservoir outflow from water level records. In this zero-outflow period, the amount of water coming into a reservoir (i.e., inflow hydrograph) can be directly quantified from changes in the reservoir water level (or water storage) after considering rainfall and evaporation rates in the reservoir water balance equation. In this step, expert knowledge, including an understanding of reservoir operation rules for flood control periods and irrigation scheduling, is applied to classify the behavior of reservoir water levels. The classified water level variations, as supplementary information, help to separate the zero-outflow periods from the nonzero-outflow periods. The partial inflow hydrograph reconstructed (for the zero-outflow periods) through reservoir water balance analysis can be used to reconstruct the outflow hydrograph of a reservoir.

2.2. Expert Knowledge and Supporting Information

2.2.1. Reservoir Water Balance

The reservoir water budget can be described using the concept of water storage mass balance, expressed as follows:

$$\frac{dS}{dt} = I - O$$  \hspace{1cm} (1)

where $S$ is the amount of water stored in a reservoir (m$^3$), $I$ is the amount of water entering the reservoir (m$^3$/s), and $O$ is the amount of water going out of the reservoir (m$^3$/s). Equation 1 can be expanded with detailed...
hydrological components to yield Equation 2 (Dang et al., 2020; Habets et al., 2018; Song et al., 2016; Vedula & Nagesh Kumar, 1996) (Figure 2):

\[
\frac{dS}{dt} = (RI + R) - (E + G + RO)
\]

where \(RI\) is the reservoir inflow from the drainage watershed (m³/s), \(R\) is rainfall on the reservoir water surface area (m³/s), \(E\) is evaporation from the reservoir water surface area (m³/s), \(G\) is the amount of stored water infiltrated through the reservoir bottom and recharged into the aquifer (or reservoir bottom infiltration, m³/s), and

1. **III-Possed Reservoir Water Balance Problem**
   - Mass balance equation: \(dS/dt = I - O \rightarrow dS/dt = (RI + R) - (E + RO)\)
   - Two unknown variables in a single equation
   - Known variables: \(S\) (from reservoir water level data), \(R\) and \(E\) (from weather data)
   - Unknown variables: \(RI\) and \(RO\)

\* \(S\) = reservoir water storage; \(I\) = total inflow; \(O\) = total outflow; \(RI\) = reservoir inflow; \(R\) = Rainfall; \(E\) = evaporation; \(RO\) = reservoir outflow

2. **Separating zero-outflow and nonzero outflow periods using expert knowledge**
   - \(RO > 0\) period identification: Cases I&II (\(RO = WS\)), III (\(RO = PS\)), and IV (\(RO = ES\))

   \* \(WS\) = Irrigation water supply; \(PS\) = principal spillway release; \(ES\) = Emergency spillway release
   - \(RO = 0\) period identification by excluding the \(RO > 0\) period

3. **Constructing partial inflow hydrographs for the zero-outflow period**
   - When \(RO = 0\) → \(RI_{RO=0} = dS/dt - R - E\) (partial inflow)

4. **Constructing complete inflow hydrographs for the entire period**
   - \(RI_{RO=0} \rightarrow RI_{RO=0}\): A rainfall-runoff model calibrated to the \(RI_{RO=0}\)
   - Complete \(RI = RI_{RO=0} + RI_{RO>0}\)

5. **Constructing complete outflow hydrographs for the entire period**
   - Mass balance equation: \(RO = -dS/dt + RI + R - E\)

**Figure 1.** Overall analysis procedure proposed to resolve the ill-posed reservoir water balance problem and quantify reservoir inflow and outflow from water level using expert knowledge.

**Figure 2.** Concept of reservoir water balance.
is the reservoir outflow from spillways (m³/s). R and E can be measured from the nearest weather station. They are negligible when the open water surface areas of a reservoir are small compared to the upstream watershed area (Deng, Liu, Guo, et al., 2015; Song et al., 2016; Uen et al., 2018). This study assumes that G is not significant because reservoir bottom infiltration has little effect on water balance, and detailed data for accurate estimation is limited (Dessie et al., 2015; Song et al., 2016).

2.2.2. Reservoir Operation Rules
Reservoir outflow (RO) can be classified into three types:

\[ RO = WS + PS + ES \]  

(3)

where WS is the water supply (m³/s), and PS and ES represent reservoir release from the principal (m³/s) and emergency spillways (m³/s), respectively. WS, PS, and ES are determined from the reservoir operation rule curve and management levels (Figures 2 and 3). The outflow components (WS, PS, and ES) can be detected from the reservoir water level observations based on an understanding of the operation rules and expert knowledge. Detailed descriptions of the operating rules are provided in Appendix A.

2.2.3. Irrigation Schedule
The water supply of the reservoir outflow (WS) is associated with agricultural irrigation implemented in the downstream areas of a reservoir. During non-rainy days, reservoir water is only released for irrigation so that crop fields are not over irrigated (Song et al., 2016; Song, Her, Jun, et al., 2019; Yoo et al., 2013). On non-rainy days, the depth of daily rainfall is even less than the amount of rainfall that does not contribute to crop water intake or an increase in soil water content, which is termed ineffective rainfall. In this study, a rainfall depth of 5 mm/day is regarded as ineffective (or ineffective rainfall) based on the information on reservoir operation practices implemented in the study areas (MAF, 1997; Song et al., 2016; Yoo et al., 2013). Irrigation stops during the interruption period even on non-rainy days, as per irrigation practice recommendations and standards (MAF, 1997; Appendix A, Figure 3).

2.3. Expert Knowledge Application Procedure
2.3.1. Inflow Reconstruction When Outflow Is Equal to Zero
When there is no water release from the reservoir (RO = 0), the water storage mass balance equation (Equation 2) can be simplified as

\[ RI_{RO=0} = \frac{dS}{dt} - R + E \]  

(4)
The inflow hydrograph reconstructed using Equation 4 covers only part of the $A_{i-1} = 0$ and $A_i = 0$; thus, it is denoted as a "partial inflow hydrograph." Even when reservoir outflow records are not available, the existence of a reservoir release can be detected by investigating reservoir water level records based on reservoir rule curve analysis (expert knowledge; Figures 3 and 4). The amount of water stored in a reservoir naturally decreases via evaporation, but rapid decreases in water level indicate reservoir spillway release. Such a water level analysis (Figures 3 and 4) also helps identify periods when the volume of impounded water increases by inflow and/or rainfall; thus, the water balance of the reservoir can be explained by Equation 4.

Reservoir water level variations caused by spillway release can be classified into four types (Figure 4). First, we detected periods when reservoir water levels decreased rapidly and monotonically, clearly indicating that there was water release (Case I). We also found that water levels lowered during the day and then jumped back to a level higher than the original at the end of the day (Case II). Additionally, there were occasions where water levels fluctuated quickly around the flood-limited water level (FLWL; Case III). In a flood control period, spillway gates are opened for extra storage and to prevent flood damage; therefore, the reservoir water levels fluctuate around the FLWL. Finally, we identified another case in which water levels increased up to the normal pool water level (NPWL). When the reservoir water level rises to the NPWL in a non-flood-control period, it remains there as long as the inflow rate is greater than or equal to the evaporation rate (i.e., equilibrium condition; Case IV).

2.3.2. Inflow Reconstruction When Outflow Is Greater Than Zero

The partial hydrographs of reservoir inflow ($RI_{RO=0}$), which were derived using the simplified mass balance equation for the period of zero outflows (Equation 4), were used as a substitute for inflow observations. A rainfall-runoff model was calibrated using these partial inflow hydrographs, and the calibrated model was then used to reproduce inflow hydrographs for the periods when outflow was greater than zero ($RI_{RO>0}$). In this study, the Tank model (Appendix B) was selected to reconstruct the inflow hydrographs due to the model's proven applicability in mountainous and monsoon climate areas (Song, Her, Park, & Kang, 2019; Yokoo et al., 2001).

![Figure 4](https://example.com/figure4.png)

**Figure 4.** Cases of reservoir water level variations revealing the existence of reservoir release. Case I: Water supply ($WS$) is equal to reservoir outflow ($RO$) and is greater than reservoir inflow ($RI$). Case II: Water supply ($WS$) is equal to reservoir outflow ($RO$) and is less than or equal to reservoir inflow ($RI$). Case III: Principal spillway release ($PS$) is equal to reservoir outflow ($RO$). Case IV: Emergency spillway release ($ES$) is equal to reservoir outflow ($RO$).
The complete $R_I$ can be reconstructed by combining the reservoir inflow hydrographs in the zero-outflow and nonzero-outflow conditions as follows:

$$R_I = R_{I_{RO=0}} + R_{I_{RO>0}}$$  \hspace{1cm} (5)

### 2.3.3. Outflow Reconstruction

The outflow ($R_O$) was then determined using the reconstructed inflow ($R_I$) and the mass balance equation as follows:

$$R_O = -\frac{dS}{dt} + (R_I + R) - E$$  \hspace{1cm} (6)

The outflow estimated in this study was divided into three components: $WS$ (water supply), $PS$ (principal spillway release), and $ES$ (emergency spillway release). These components were taken from reservoir operation rules (Section 2.2.2 and Appendix A) and reservoir rule curves (Figure 3).

### 2.4. Conventional Benchmark Methods (Without Expert Knowledge)

In this study, we compared the performance of the newly proposed approach (Proposed) and two conventional approaches (Conventional I and II) in terms of accuracy and uncertainty to demonstrate the Proposed method's applicability. As described above, the Proposed method quantifies reservoir inflow and outflow from observed water levels; thus, the Proposed method does not simulate zero outflows and water level but rather uses them as input data. In contrast, the Conventional methods estimate reservoir inflow (Conventional I) and outflow (Conventional II) using regionalized hydrological models (a Tank model for inflow and a reservoir operation model for outflow). Conventional I method uses water level observations to estimate outflow from the mass balance equation, with inflow estimates made using a regionalized Tank model. Conventional II method uses a regionalized reservoir operation model to predict reservoir outflow and then estimates inflow from the outflow estimates and mass balance relationship. All three methods use a Tank model to calculate reservoir inflow. The Proposed method calibrates a Tank model to partial reservoir inflow hydrographs derived from the mass balance (Equation 4). Conversely, Conventional I method employs a Tank model with parameter values that are determined based on the relationship between watershed landscape and parameter values calibrated to other gauged watersheds (known as a regionalized Tank model). Conventional II method also calibrates a Tank model to reservoir inflow estimates made using the mass balance and a reservoir operation model with parameters that are adjusted in relation to the irrigation practices of downstream farms.

#### 2.4.1. Conventional I (Inflow Approximation First With Regionalized Tank Model)

The Conventional I method estimates reservoir inflow using a regionalized rainfall-runoff model that does not require calibrating parameter values (Beck et al., 2016; Prieto et al., 2019). Parameter calibration is often not an option due to the absence of reservoir inflow measurements. In such a case (ungauged areas), model parameter values can be estimated from the statistical relationships between watershed characteristics and parameter values derived from gauged watersheds, often called regionalization. This study incorporated parameter values regionalized from the previous studies into a Tank model (Appendix B), and the Conventional I method used the regionalized Tank model to quantify reservoir inflow from the drainage watershed (Amiri et al., 2016; H. Y. Kim & Park, 1988; Song, Her, Suh, et al., 2019; Yokoo et al., 2001). The parameter values of the Tank model were predetermined as a function (i.e., regression equation) of watershed characteristics, including drainage areas and land covers (H. Y. Kim & Park, 1988). Regression relationships and regionalized models have been widely employed for the design, planning, and management of reservoirs (Amiri et al., 2016; H. Y. Kim & Park, 1988; Song et al., 2016; Song, Her, Suh, et al., 2019; Yokoo et al., 2001), but regionalized parameters are subject to errors and uncertainty (Pool et al., 2019; Song, Her, Suh, et al., 2019). Once inflow hydrographs are constructed using the regionalized model, reservoir outflow can be calculated from the water balance equation (Equation 6).

#### 2.4.2. Conventional II (Outflow Approximation First With Regionalized Reservoir Operation Model)

The Conventional II method attempts to resolve the ill-posed problem by estimating the outflow of a reservoir using a regionalized reservoir operation model. The reservoir operation model estimates reservoir outflow by calculating irrigation water requirements for non-rainy days as well as excess water to be released during
storm events, and it is common to find its parameter values from literature or to regionalize these values according to watershed characteristics (Haddeland, Skaugen, & Lettenmaier, 2006; Song et al., 2016; Yassin et al., 2019; Appendix C). For example, the water requirement for rice paddy fields can be determined by estimating the daily water demand necessary to maintain optimal water levels for paddy rice growth during a cropping period. The water requirement is calculated as a function of meteorological data and farming practices (Nam & Choi, 2014; Song, Her, Jun, et al., 2019). Then, reservoir inflow can be estimated using a Tank model calibrated to reservoir water levels and the reservoir water balance budget (Deng, Liu, Liu, et al., 2015; Kang & Park, 2014; Song et al., 2016). Unlike Conventional I, Conventional II calibrates the parameters of a Tank model by comparing estimated reservoir water levels to observed levels. The reservoir water level is estimated or derived from the reservoir water balance equation incorporating inflow (simulated using the Tank model) and outflow (i.e., irrigation water requirement, calculated using the regionalized reservoir operation model). The Conventional II method has been widely used as a decision-making tool for reservoir operations in various regions, including the United States, China, Turkey, and South Korea (Gorguner & Kavvas, 2020; Haddeland, Lettenmaier, & Skaugen, 2006; Kang & Park, 2014; Wu & Chen, 2013). Both Conventional I and II methods use regionalization approaches to relax the ill-posed water balance equation (Conventional I: regionalized Tank model for inflow estimation vs. Conventional II: regionalized reservoir operation model for outflow estimation); in contrast, the Proposed approach divides an analysis or modeling period into sub-periods and applies expert knowledge to simplify the equation.

3. Application

3.1. Study Watersheds and Reservoirs

The Proposed method for reconstructing inflow and outflow reservoir hydrographs was applied to four reservoirs and their upstream watersheds in South Korea (Figure 5 and Table 1). The four reservoirs receive water drained from their upstream watersheds, which are mainly covered with a forest of 25.3–91.3 km² (equivalent to 54%–87% of the watershed areas). The reservoirs were constructed in the 1960s and 1970s to supply water to rice paddy fields irrigated downstream and to protect downstream areas from flooding by storing excessive runoff from the upstream watersheds. The volume of water stored in the reservoirs usually decreases due to irrigation in the rice-growing seasons from April to September. When heavy rainfall events arrive in July and August, the reservoir levels rise as a result of relatively high reservoir inflow and low irrigation requirements.

3.2. Performance Evaluation

The accuracy of reservoir inflow, outflow, and water level simulated using the proposed method was compared to that of the Conventional I and II methods (Table 2). In this study, potential errors and uncertainty in observations such as reservoir water levels were not considered in the evaluation. The partial reservoir inflow was regarded

Table 1

| Reservoir  | Drainage area (km²) | Irrigated area (km²) | Effective storage (x10⁴ m³) | NPWL (m) | FLWL (m) | DL (m) | Management objective | Data period |
|------------|---------------------|----------------------|-----------------------------|----------|----------|--------|----------------------|-------------|
| Idong      | 91.3                | 17.9                 | 2,091                       | 45.0     | 43.05    | 33.3   | IR (rice paddy fields) and FC | 2001-2015   |
| Gopung     | 25.3                | 12.9                 | 782                         | 85.0     | 83.7     | 62.0   | IR (rice paddy fields) and FC | 2011-2014   |
| Gosam      | 68.2                | 29.7                 | 1,522                       | 52.4     | 51.9     | 40.7   | IR (rice paddy fields) and FC | 2011-2014   |
| Cheongcheon| 67.5                | 26.4                 | 2,075                       | 40.2     | 38.7     | 23.2   | IR (rice paddy fields) and FC | 2011-2014   |

Note. NPWL: normal pool water level (Figure 2); FLWL: flood-limited water level (Figure 2); DL: deal level; IR: irrigation; FC: flood control.
as an observation because it was derived from the mass balance relationship (see Equation 4 in Section 2.3.1) that only involves observations of rainfall and evaporation from the reservoir water surface area. We used rainfall and evaporation (pan evaporation) measurements made at the nearest weather station (Figure 5). Such weather measurements can include errors and uncertainty, but these were not considered in this study. The uncertainty of rainfall-runoff modeling (i.e., Tank modeling) was quantified using the generalized likelihood uncertainty estimator (GLUE) approach (Beven & Binley, 1992; Her & Heatwole, 2016). The $E_{NS}$ and $E_{NS,log}$ (Appendix D) thresholds of 0.90 and 0.65 were used to identify behavioral solutions in the Tank model calibration, and $E_{NS}$ of 0.65 was employed to analyze uncertainty in estimating reservoir water levels. The high threshold values were selected to ensure the accuracy of the reservoir mass balance analysis. The average range of behavioral simulation variations was then calculated to measure the amount of uncertainty in reservoir inflow and outflow estimates.

The accuracy and uncertainty assessment were separately conducted during zero-outflow and nonzero-outflow periods that were identified based on the investigation of reservoir water level variations (Cases I to IV in Figure 4; Table 2). As described previously, when reservoir outflow was zero (or the zero-outflow condition), reservoir inflow data derived from the mass balance equations (Equation 4) was regarded as observations. On the other hand, when outflow was greater than zero (or the nonzero-outflow condition), there was no inflow observation (inflow could not be derived from Equation 4 because it becomes an ill-posed problem). In this case, accuracy could not be evaluated, but the uncertainty of the proposed approach was quantified by investigating the uncertainty of the calibrated Tank model used to reconstruct complete inflow hydrographs. Zero outflows is observation itself, and reservoir water levels are also direct observations. When these observations were unavailable, as in the cases of inflow and outflow in nonzero-outflow periods, this study could only assess the uncertainty but not the accuracy of the approaches.

The accuracy of the Tank model calibrated to the inflow observations derived from Equation 4 (the mass balance equation for the zero-outflow condition) was quantified using multiple statistics, including the efficiency coefficients for flow ($E_{NS}$), log-transformed flow ($E_{NS,log}$), flow duration curve ($E_{NS,FDC}$), and a runoff coefficient representing the ratio of runoff to rainfall (Appendix D). Song (2017) and Song, Her, Suh, et al. (2019) reported that undisturbed Korean humid ($\frac{\sum PET}{\sum Rain} \leq 0.65$) and mountainous (average slope $\geq 15\%$) watersheds have runoff coefficients ranging from 56% to 80%. The reported runoff coefficients were used as supplementary information to evaluate the water balance analysis. During the model calibration, a sampling-based heuristic optimization algorithm, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), was used to explore the parameter space of the Tank model and to identify behavioral parameter value sets (Deb et al., 2002; Appendix E). Two objective functions, $E_{NS}$ and $E_{NS,log}$, were employed to balance the calibration for high and low flow (Table D1).
4. Results

4.1. Period Separation

The periods of time in which reservoir level changes were attributed to inflow only \((RO = 0)\) were identified by excluding the cases in which water release was reasonably assumed to take place for irrigation or flood control (Figure 4, Cases I to IV) during the simulation period (Figure 6 and S1 in Supporting Information S1). The observed water levels were then converted into reservoir inflow rates using the simplified water balance equation (Equation 4). In the case of Idong, the number of identified inflow-only days ranged from 75 to 179 days per year, and 66%–99% of the daily inflows fell between 0.1 mm/day and 1.0 mm/day, indicating the significance of low flow to the reservoir water balance. The derived partial inflows also included a few days of medium flow (10–50 mm/day) and high flow (greater than 50 mm/day). The derived partial inflow hydrographs were further split into two periods: P1 (e.g., 998 inflow-only days between 2008 and 2015 for Idong) and P2 (e.g., 706 inflow-only days between 2001 and 2007 for Idong). Then, the Tank model's parameters were calibrated to the inflows of P1 that includes the driest and wettest seasons so that the models' ability and parameter spaces could be thoroughly explored (Gan et al., 1997; Moriasi et al., 2007; Song, Her, Park, & Kang, 2019).

4.2. Inflow

4.2.1. Zero Outflow

A Tank model was calibrated to partial reservoir inflow hydrographs derived from the reservoir water balance equation (Equation 4) when there was no outflow (the zero-outflow condition; Figure 7). The calibrated Tank model outperformed the Conventional methods (Figures 7 and 8) in all four study areas for both calibration and validation periods. The calibrated model reproduced high and low flow at acceptable accuracy levels (median \(E_{NS} = 0.71\) to 0.95 and median \(E_{NS,Log} = 0.60\) to 0.90; Moriasi et al. [2015]; Ritter & Muñoz-Carpena [2013]) and flow variability at the median \(E_{NS, FDC} = 0.77\) to 0.98. The predicted runoff coefficients (58%–66%) were within the range of the reported values (56%–80%; Song [2017]; Song, Her, Suh, et al. [2019]; Figure 7).

The Conventional methods sometimes yielded poor performance, especially in predicting low flow, which is critical to long-term reservoir water budgeting. The Conventional II method performed relatively poorly in the
Figure 7. The Pareto fronts derived from the Tank model calibration implemented using the multi-objective optimization algorithm (NSGA-II).

Figure 8. The accuracy statistics of reservoir inflow predicted using the Proposed and Conventional I and II methods when outflow is equal to zero. A parameter set of the Tank model that provided the highest accuracy statistics ($E_{NS} + E_{NS,log}$) in the calibration period was selected for this comparison.
prediction of reservoir inflow (low $E_{NS,Log}$ compared to those of the other two methods). The performance statistics of the two Conventional methods varied substantially according to the study reservoirs. For example, the Conventional I method relatively accurately predicted low reservoir inflow at Gopung, but its low flow prediction was poor for Idong. The Conventional II method also relatively accurately predicted the high inflow of Gopung, but its performance was not acceptable in the case of Gosam. In contrast, the calibrated Tank model that was part of the proposed method produced consistently acceptable accuracy for all the study reservoirs, demonstrating its applicability.

The amount of uncertainty in reservoir inflow predictions made using the Proposed method was much smaller than the uncertainty of the Conventional II method when there was zero outflow (Figure 9 and Table 3). For example, the uncertainty bands of reservoir inflow predicted using the Conventional II method were 4.8 times to 8.8 times wider than those of the Proposed method (Table 3). In addition, the uncertainty bands of Conventional II were large enough to cover zero inflow (even when the observations were not zero) and 50 times larger than

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**Figure 9.** Comparison of reservoir inflow (or watershed runoff) hydrographs predicted using the Proposed and Conventional methods and their uncertainty. The shaded areas (in gray) refer to the nonzero-outflow conditions or periods.
the observations. The uncertainty bands of both the Proposed and Conventional II methods tended to be wider when inflows were high (Figure 9), even though $E_{NS}$ (known to be sensitive to large values) and $E_{NS,log}$ (relatively less sensitive to large values compared to $E_{NS}$) were equally weighted in the calibration. However, the relative size of the uncertainty (shown in the log scale; Figure 9) decreased with increases in reservoir inflow rates. In other words, the Conventional II method resulted in more uncertainty in a recession limb and a baseflow period compared to the Proposed method. These results imply that the Conventional II method may not be able to accurately predict reservoir inflow, especially regarding low flow, which is critical to a long-term reservoir water budget. The uncertainty involved in the Conventional I method could not be calculated as there was no information about the uncertainty of the regionalized relationships used to prepare the Tank model.

### 4.2.2. Nonzero Outflow

The Tank model calibrated to the derived partial inflow hydrographs under the zero-outflow condition was used to reproduce reservoir inflow when outflow was greater than zero (Figure 9). Since there were no inflow observations in the nonzero-outflow condition (Table 2), the accuracy of the reservoir inflow estimates made using the Proposed and Conventional approaches could only be compared to each other rather than evaluated independently. The Conventional I approach estimated a smaller amount of inflow compared to the proposed method. For example, the runoff coefficients calculated from the reservoir inflow of Conventional I were smaller (51%–55%) than the reported values (56%–80%; Song [2017]; Song, Her, Suh, et al. [2019]). However, the runoff coefficients provided by the Proposed (60%–65%) and Conventional II (60%–72%) methods were within the range of the reported values (56%–80%).

The uncertainty band of inflow estimates made using the Proposed method was much smaller than that of the Conventional II method (Table 3), which is similar to the uncertainty band found when outflow was equal to zero. The amount of uncertainty in inflow estimates made using the Conventional I method could not be calculated as there was no information about the uncertainty of the regionalized Tank model.

### 4.3. Outflow

#### 4.3.1. Zero Outflow

Complete reservoir outflow hydrographs were constructed using the reservoir routing equation (Equation 6) based on predicted inflow and observed reservoir water levels (Figure 10). When there is zero outflow, the Proposed method does not try to predict the outflow but rather accepts it as an observation. Such modeling flexibility is attributed to the fact that the Proposed method separates the prediction periods according to a given understanding of reservoir hydrology and operation rules (Figures 2–4). However, the Conventional methods still attempt to predict reservoir outflow.
outflow even when zero outflow is observed. For instance, outflow estimates made using the Conventional I method were consistently larger than zero. In the case of Gosam, the Conventional I method underestimated reservoir inflow significantly enough to make outflow estimates become negative in the mass balance equation (Equation 6). In this case, the negative outflow values were replaced with zero, which is why Conventional I reproduced the zero outflow of Gosam but failed to predict the zero outflow of the other reservoirs. In contrast, the Conventional II method overestimated reservoir inflow (i.e., reservoir water levels predicted using the Conventional II method were greater than the observed levels) when zero outflow was observed. This inflow overestimation resulted in outflow greater than zero (i.e., outflow overestimation) even when no outflow was observed. The Proposed method regards zero outflow as an observation with no uncertainty. The Conventional II method produced a large amount of uncertainty in the reservoir outflow estimates, ranging from zero to 190 mm/day even when zero outflow was observed.

4.3.2. Nonzero Outflow

The accuracy of the reservoir outflow estimates was evaluated by comparing the estimates made using the three different methods because there was no outflow observation made in the nonzero-outflow condition (Figure 10). Compared to the Proposed method, the Conventional I and II methods estimated a relatively small amount of outflow...
Peak outflow timings predicted by the three methods were similar to each other, which led to a strong correlation between the outflow hydrographs (r of 0.71 to 0.97; Figure 10). However, the peak outflow rates predicted using the methods were substantially different from each other. The peak outflow rates predicted by the Proposed method tended to fall between the rates of the Conventional methods (Figure 10). The size of the uncertainty predicted in the inflow and outflow hydrographs using the Proposed method (0.7–1.3 m/day) was smaller than that of the Conventional II method (1.1–4.4 m/day; Table 3 and Figure 10). In the case of the Conventional I method, outflow uncertainty could not be calculated as there was no uncertainty information for the regionalized Tank model.

4.4. Water Level

The Proposed and Conventional I methods use reservoir water level observations as input data to estimate inflow and outflow; thus, the accuracy and uncertainty of their water level estimates were not evaluated in this study. The Conventional II method estimated the reservoir water level at the accuracy levels of $E_{NS}$ 0.69 to 0.94 (Figure 11). The acceptable accuracy of water level modeling did not always lead to acceptable reservoir inflow prediction accuracy due to the characteristics of reservoir water balance at the NPWL or FLWL (Figures 2 and 3). In the case of Gosam, for example, the Conventional II method accurately ($E_{NS}$ of 0.94) reproduced water level but failed to reproduce inflow ($E_{NS} < 0$; Figure 8). As long as the rate of water inflow is greater than that of evaporation from the reservoir water surface once a reservoir is filled with water, the reservoir water level is maintained at the NPWL, and thus the accuracy of the water level prediction is not affected by errors in the inflow estimates. The width (or size) of the inflow uncertainty band ranged from 0.46 to 1.54 m/day depending on the reservoirs. The water level uncertainty for Cheongcheon (0.46 m/day) was smaller than that of the other three reservoirs (1.16–1.54 m/day; Table 3), which may be attributed to the fact that Cheongcheon's inflow uncertainty was relatively lower in the refill periods (Figure 3) compared to that of the other reservoirs.
5. Discussion

This study demonstrated how expert knowledge and hydrological reasoning can help water balance analysis to predict reservoir behavior and regulate hydrological modeling for improved accuracy and reduced uncertainty in reservoir analysis. The hydrological periods of a reservoir can be categorized based on the understanding of reservoir operation and investigation of reservoir water level records so that additional information can be derived to resolve the ill-posed water balance equation. The identification of zero-outflow periods allowed reservoir inflow to be directly related to changes in reservoir water levels, and derived partial inflow hydrographs enabled the prediction of reservoir inflow and outflow for the entire analysis period, including times when outflow was greater than zero.

The Proposed method relaxes the ill-posed reservoir water balance equation by identifying periods when inflow (an unknown variable) can become a direct function of water level (a known variable). The expert knowledge (Cases I, II, III, and IV in Figures 2–4 and Equations 1–6) explains the variations in reservoir water level and then links them to the simplified water balance equation. These hydrological reasoning processes can generate additional data to build a complete inflow hydrograph for the entire analysis period. The results demonstrate that the Proposed method using existing hydrological knowledge outperformed the Conventional approaches that rely on the model regionalization (Figures 7–11 and Table 3), highlighting its applicability.

The incremental benefit of applying the expert knowledge was quantified by excluding each of the reservoir water level variation cases in turn (Figures 4 and 12). For example, when the reservoir inflow hydrographs were derived without considering Case III (water level is maintained at FLWL due to the principal spillway release; see Figure 4), the flow prediction performance was degraded from an $E_{NS}$ (high flow) of 0.93 to 0.71 and an $E_{NS,\log}$ (low flow) of 0.53 to 0.39 (Figure 12), indicating the importance of information regarding the operation of the principal spillway (or reservoir operation for flood control) in reservoir water balance analysis. When excluding Case II (water level increases even with water release for irrigation water supply; see Figure 4), inflow prediction accuracy was also decreased from an $E_{NS}$ (high flow) of 0.93 to 0.86 and an $E_{NS,\log}$ (low flow) of 0.53 to 0.35 (Figure 12). Compared to the previous case (excluding Case III), low flow prediction accuracy was more severely degraded (0.53–0.39 vs. 0.53 to 0.35), which implied that irrigation water supply is also critical for reservoir analysis, especially in dry periods. When excluding Case IV (water level is maintained at NPWL due to emergency spillway release; see Figure 4), the level of accuracy degradation was minimal, from an $E_{NS}$ (high flow) of 0.93 to 0.92 (Figure 12), because only a few periods of high flow were observed when the reservoir water level was maintained at NPWL. Ignoring Case I (water level decrease due to water release for irrigation water supply; see Figure 4) would be unrealistic in practice and was therefore not tested in this study.

The Proposed method outperformed the Conventional I and II methods in terms of both accuracy and uncertainty. Overall, the parameter values of the Conventional I method were not within the range of the Proposed method (Figure 13); one reason for this disagreement might be that Conventional I employs a regionalized Tank model. Regionalized models attempt to predict variables of interest-based on the relationships between parameter values and landscape characteristics developed in other watersheds. Thus, their outputs inherently include a great deal of uncertainty, but usually, the amount of this uncertainty is not quantified due to a lack of information and data. Additionally, regionalized relationships tend to have outliers that cannot be adequately explained. For example, one parameter may show a clear correlation with a particular watershed characteristic, but other watersheds can behave very differently from the general trend (e.g., Jan Seibert, 1999; Wagener & Wheater, 2006).

The Conventional II method provided much wider ranges of the model parameter values (i.e., greater parameter uncertainty) compared to the Proposed method (Figure 13), which is attributed to the fact that when water levels reach the flood management level (NPWL or FLWL), reservoir outflow is no longer a function of water level to which the Tank model of Conventional II is calibrated (Section 4.4). When the reservoir water level is maintained at the flood management level, reservoir water release calculated using Conventional II becomes a direct function of inflow estimates made using a calibrated Tank model. Unlike Conventional II, the Proposed method calibrates a Tank model only in the zero-outflow periods and thus improves the accuracy of inflow estimation. When zero outflow is observed, for instance, inflow can be more accurately estimated from reservoir water level records because inflow can be directly related to the observed water level. However, it is difficult to accurately observe or estimate the amount of water released from a reservoir for flood control (or when the water level reaches NPWL or FLWL). As such, the Conventional II method should include more uncertainty in its outflow estimates than the Proposed method. When reservoir water levels were lower than the flood management levels, reservoir water
was released only for irrigation water supply, which is determined using the regionalized reservoir operation model. Thus, the uncertainty of irrigation water supply estimated using Conventional II cannot be quantified as the regionalized model does not have uncertainty information, which is similar to the case of using a regionalized Tank model of Conventional I for inflow estimation.

This study demonstrates that incomplete information—such as reservoir inflow hydrographs partially derived from the mass balance when zero outflow was observed—can help improve the accuracy of reservoir analysis. Past studies have shown that the use of a limited number of streamflow observations can aid in the development of complete runoff hydrographs (e.g., Etter et al., 2018; U. Kim & Kaluarachchi, 2009; Perrin et al., 2007; Seibert & Beven, 2009). These studies have also found that partial streamflow data carefully collected from both wet and dry seasons could be sufficient to achieve acceptable model performance. Previous research has focused on investigating how many observations or how much variability from peak to base flows is required to obtain acceptable calibration accuracy rather than gleaning additional data and information from other partially known variables. Recent studies have attempted to derive information from various sources of data, such as remotely sensed products (e.g., Dembélé et al., 2020; Huang et al., 2020; Nijzink et al., 2018), isotope tracers (e.g., Holmes et al., 2020), and crowdsourced data (e.g., Avellaneda et al., 2020; Weeser et al., 2019), and they have found that the derived information can improve the prediction accuracy of hydrological processes. Reservoir water levels are direct observations, but they have not often been used for reservoir analysis, presumably due to the lack of a framework for the efficient use of such data. This study proposed a means of linking reservoir water level data to inflow and outflow, which is expected to make existing reservoir water data more useful.

Figure 12. Performance of the proposed framework (a) with Cases I, II, III, and IV (original); (b) without Case II; (c) without Case III; and (IV) without Case IV.
Constraining the parameter space using expert knowledge can also help to regulate the behavior of a hydrological model and reduce modeling uncertainty when direct observations are not available. Gharari, Shafiei, et al. (2014) and Hrachowitz et al. (2014) proposed a framework to constrain the parameter space of a hydrological model using existing knowledge rather than arbitrarily adjusting parameter values for ungauged basins. In their studies, the types of parameters to be calibrated were identified using parameter and process constraints determined using expert knowledge. The parameter constraints limited the solution space according to the relationships that must be held between the different types of model parameters. For instance, in the Tank modeling of this study, the sum of the first tank's outlet coefficients (representing the ratio of quick flow to storage) may be greater than that of the second tank's outlet coefficient (which controls intermediate flow) in mountainous areas where flow velocities for quick flow are usually greater than those for intermediate flow (Appendix B): \( a_2 < b_1 \). The process constraint used soft data or information about the behavior of a system, such as runoff ratios (e.g., \( 56% \leq \text{ERC} < 80% \)) in this study. Hrachowitz et al. (2014) demonstrated that an uncalibrated but constrained complex model yielded levels of model performance and uncertainty similar to those of a calibrated but unconstrained standard lumped model. As various types of remotely sensed data emerge (e.g., soil water content and water levels) and hydrological information and knowledge accumulate, soft data is expected to be used to a greater extent to complement hard calibration in hydrological analysis (Akbar et al., 2020; Huang et al., 2020; Mao et al., 2020). Advanced uncertainty and sensitivity analysis methods such as a global sensitivity analysis (Razavi et al., 2021; Sheikholeslami et al., 2019) may help reduce the parameter spaces by identifying a dominant group of parameters that significantly contribute to variability in model outputs (see Figures S2 and S3 in Supporting Information S1 for more information).

Reservoirs in hydrological systems have significantly altered natural flow regimes by storing and releasing water; however, these effects have not been a focus of hydrological analysis (Payan et al., 2008; Volpi et al., 2018; Yassin et al., 2019). Without accurate representations of reservoir processes and their hydrological impacts, hydrology and land surface models may fail to be useful tools for water resources planning and management. Reservoir modeling and analysis have been a challenge in hydrological modeling due to the complexity of reservoir operation and the behaviors associated with natural variations and human activities, such as flooding and irrigation.

**Figure 13.** Normalized behavioral parameter value sets of the Tank model (for reservoir inflow estimation using the Proposed and Conventional I and II methods) and their interrelationships. (a) Idong, (b) Gopung, (c) Gosam, and (d) Cheongcheon. The parameter values were normalized by their value ranges (Table B1).
This study has demonstrated that expert knowledge about reservoir operations combined with hydrological reasoning (reservoir water balance) and supplementary observations (reservoir water levels) can construct a full picture of reservoir hydrology, including mass curves and flow duration curves (Appendix F; Figure F1). The proposed methods can thus facilitate reservoir analysis for water resources and management and help increase analysis accuracy, especially in data-limited areas.

6. Limitations and Future Work

This study proposed a new approach to reconstructing reservoir inflow and outflow hydrographs from water level data using expert knowledge, soft data, and hydrological reasoning. In the application, the new method demonstrated its efficacy. However, the Proposed approach may not be directly and/or universally applicable due to assumptions and simplifications made to accommodate for the lack of information typically present with reservoir operation and monitoring. For instance, this study selected headwater reservoirs that do not have large upstream reservoirs. Thus, reservoir inflow is assumed to be naturally created (vs. released from the upstream reservoir) and transported from the upstream drainage areas of the interested reservoir. When analyzing a series of reservoirs located along a streamline in a large drainage basin (Kang & Park, 2014; Nazemi & Wheater, 2015), the proposed framework should be applied to the most upstream reservoir first, and then the estimated outflow of the reservoir should be considered as part of inflow to the second-most upstream reservoir (or a reservoir located right downstream of the headwater reservoir) using hydrological/hydraulic channel routing models (Bentura & Michel, 1997). Moving further downstream, additional hydrological processes and management practices—such as irrigation return flow from agricultural areas (especially rice paddies), water withdrawal from river channels (for irrigation and municipal/industrial water supplies), the interaction between groundwater and river flow, and transmission loss—may influence reservoir inflow/outflow estimation (Payan et al., 2008; Pokhrel et al., 2016; Zhao et al., 2016). The Proposed approach does not explicitly consider these additional processes and practices but treats them lumped at reservoir inflow. For example, partial inflow hydrographs derived from reservoir levels (when zero reservoir outflow is observed or expected) contain the contributions of the additional processes and practices, and the parameters of a Tank model are calibrated to the partial inflow to reconstruct full reservoir inflow hydrographs. Their contributions are mixed in the calibration process, which can add additional errors and uncertainty to the inflow estimation.

There are other assumptions that might also add uncertainty to the analysis results. Rainfall and evaporation measurements made at the nearest weather stations might not accurately represent the weather conditions of the study areas mainly due to the distance between the study areas and the stations and the spatial variability of weather variables. The potential errors and uncertainty of rainfall and evaporation data were not considered in this study. Reservoir bottom infiltration was assumed to have little effect on the reservoir water balance based on existing literature (Dessie et al., 2015; Song et al., 2016). In the case of a reservoir that has a small surface area, rainfall and evaporation measurement uncertainty and the zero bottom infiltration assumption might not significantly affect a reservoir water budget analysis (Deng, Liu, Guo, et al., 2015; Song et al., 2016; Uen et al., 2018). The drainage area to surface area ratios of the study reservoirs ranges from 0.025 (Gopung) to 0.039 (Cheongcheon), which are relatively small compared to the average ratios of 0.182 for 3,239 lakes and reservoirs located in the US and 0.063 for 1,337 European lakes (Nõges, 2009; Rodgers, 2017).

The reservoir operating rules, including operation periods, management water levels, and ineffective rainfall depth, is another source of uncertainty. This study adopted the reservoir operation standards (MAF, 1997), but the standards may not be always followed by an operator. Reservoir managers often apply personal judgments to decide the amount and timing of water release (Coerver et al., 2018; Ngo et al., 2008; Song, Her, Jun, et al., 2019). The discrepancy between the assumption (or the operation standard) and practices that were actually implemented to control a reservoir could add error and uncertainty to this study's reservoir analysis.

The Proposed approach requires reservoir water level data to reconstruct inflow and outflow hydrographs. This study included four reservoirs in the application of the Proposed approach. The four reservoirs cannot hydrologically represent all other reservoirs around the world. In addition, reservoir water level records are not always available, and reservoir data and water level records are often limited in many parts of the world (Gao et al., 2012; Turner et al., 2020; Yassin et al., 2019). For example, privately owned small reservoirs usually do not have (or provide) reservoir data. In addition, it is difficult to obtain such data for large reservoirs because of security reasons, especially where water conflicts exist between (local and national) governments (e.g., trans-
boundary river basins) and multiple-use interests are involved (e.g., irrigation vs. municipal water supply; Habets et al. [2018]; Han et al. [2020]; Song, Her, Jun, et al. [2019]). However, reservoir water level records may be relatively easy to obtain compared to reservoir inflow and outflow data. Advanced remote sensing technologies have helped monitor the water levels of waterbodies including reservoirs (Avisse et al., 2017; Gao et al., 2012; Pipitone et al., 2018), and the Proposed approach is expected to benefit from advances in water level sensing.

7. Conclusion

This study proposed a framework to resolve the ill-posed water balance equation by carefully investigating the behavior of reservoir water levels and constraining hydrological models. In this study, expert knowledge, soft data, hydrological reasoning, and modeling were systematically employed to generate new data and information required to draw a complete picture of the reservoir water budget. The following points were found:

1. Expert knowledge, including an understanding of reservoir operation, can be used to classify zero-outflow and nonzero-outflow periods; additionally, the identification of zero-outflow periods can be used to reconstruct partial inflow hydrographs based on changes in reservoir water levels
2. Partial inflow hydrographs can be used to estimate inflow and outflow in the nonzero-outflow period with reservoir mass balance and hydrological modeling
3. The benchmark approaches (Conventional I and II) employed to estimate reservoir inflow and outflow hydrographs in an ungauged watershed did not yield an acceptable performance in this study
4. The Proposed method estimated continuous reservoir inflow and outflow from water level records, and it outperformed the Conventional methods with improved accuracy and reduced uncertainty

This study opens a wide range of opportunities regarding how future studies for reservoir management and operation can be designed to efficiently quantify reservoir water balance dynamics. The proposed framework is expected to improve understanding of reservoir hydrology and aid water resources planning by enabling the reconstruction of reservoir routing processes from water level records.

Appendix

A. Reservoir Operation Rule

1. In crop-growing periods, reservoir water is released only to provide the irrigation water supply ($WS$). The crop-growing period consists of the interruption and drawdown periods
2. In the interruption period, $WS$ stops even when it is in the middle of the crop-growing period (zero-outflow period)
3. In the drawdown periods, reservoir water is released through the drainage spillway (Figure 2) to supply irrigation water for the downstream areas
4. When the reservoir level decreases below the dead level ($DL$), $WS$ stops (zero-outflow period)
5. In the flood control period, the principal spillway release ($PS$) is made to accommodate space for excess water inflow to prevent the reservoir water level from exceeding the flood-limited water level ($FLWL$)
6. When the irrigation periods overlap with the flood control periods, priority is given to flood control in reservoir operations; thus, $WS$ is released only when the reservoir water level ($WL$) drops below the $FLWL$ to protect downstream areas from flooding
7. In the non-flood control and non-crop-growing periods, the reservoir collects inflow from its upstream drainage areas (or watershed) until its water level reaches the normal pool water level ($NPWL$) for water supply during the next growing period
8. In the non-flood control period, when reservoir water level exceeds the $NPWL$, the surcharge water ($ES$) is discharged through the normal pool spillway

B. Tank Model

A Tank model with three storages (H. Y. Kim & Park, 1988; Song, Her, Park, & Kang, 2019; Sugawara, 1979) was prepared to simulate the streamflow of the study watershed (the drainage areas of a study reservoir). The
Tank model consists of three vertical tanks with outlets located at the bottom and side of each tank (Figure B1 and Table B1; Song, Her, Park, & Kang, 2019). Water running out of the side outlets of the tanks represents surface runoff (for the first or top tank), intermediate runoff (for the second tank), and groundwater flow (for the bottom tank; H. Y. Kim & Park, 1988; Song et al., 2016; Song, Her, Park, & Kang, 2019). The Tank model gave a strong performance in predicting the streamflow of watersheds with various hydrological conditions in East Asia, including watersheds in South Korea, Japan, and Taiwan (Chen et al., 2014; Fumikazu et al., 2013; Song et al., 2016; Song, Her, Park, & Kang, 2019; Yokoo et al., 2001). Additionally, the Tank model has been widely used for drainage watersheds of reservoirs where flow travel time is short and the recession limb of the streamflow hydrograph is steep (Song et al., 2016). Actual evapotranspiration (AET) is estimated using the Penman-Monteith (PM) approach (Allen et al., 1998), crop coefficients (Allen et al., 1998; Song, Her, Park, & Kang, 2019), and a soil evaporation compensation parameter (SECP; Song, Her, Park, & Kang, 2019; Song, Her, Suh, et al., 2019). The ranges of parameter values were determined by considering the characteristics of Korean mountainous watersheds and were used as constraints for optimization (or calibration).

![Figure B1. Model structure of the Tank.](image)

**Table B1**

| Parameter | Description | Min. | Max. |
|-----------|-------------|------|------|
| $a_{11}$  | Side-outlet coefficient for the 1st side outlet in the 1st tank (dimensionless) | 0.08 | 0.5 |
| $a_{12}$  | Side-outlet coefficient for the 2nd side outlet in the 1st tank (dimensionless) | 0.08 | 0.5 |
| $h_{11}$  | Height of side outlet for the 1st side outlet in the 1st tank (mm) | 5 | 60 |
| $h_{12}$  | Height of side outlet for the 2nd side outlet in the 1st tank (mm) | 20 | 110 |
| $b_{1}$   | Bottom-outlet coefficient for the 1st tank (dimensionless) | 0.1 | 0.5 |
| $a_{2}$   | Side-outlet coefficient in the 2nd tank (dimensionless) | 0.03 | 0.5 |
| $h_{2}$   | Height of side outlet in the 2nd tank (mm) | 0 | 20 |
| $b_{2}$   | Bottom-outlet coefficient for the 2nd tank (dimensionless) | 0.01 | 0.35 |
| $a_{3}$   | Side-outlet coefficient in the 3rd tank (dimensionless) | 0.003 | 0.03 |
| $SECP$    | Soil evaporation compensation parameter | 0.001 | 0.1 |
C. Reservoir Outflow Estimation in Conventional II Method

The Conventional II method estimates $WS$ based on the irrigation water requirement ($IWR$) concept combined with a paddy water balance analysis (Kang & Park, 2014; Nam & Choi, 2014; Song, Her, Jun, et al., 2019). The $WS$ consists of the $IWR$ and delivery management water requirement ($DMWR$; J.-S. Kim et al., 2005; Song, Her, Jun, et al., 2019). The irrigation efficiency ($Es$) is used to determine the $DMWR$. $Es$ represents the relative portion of agricultural water delivered to the target paddy fields, and it considers the combined efficiency of the water conveyance and distribution systems (Bos & Nugteren, 1990; Jensen, 2007; Song, Her, Jun, et al., 2019). The $WS$ is calculated using the following equation (Georgiou & Papamichail, 2008; Song et al., 2016; Song, Her, Jun, et al., 2019):

$$WS = \frac{1}{86400} \times \frac{A_{irr}}{Es} \times \frac{IWR}{1000}$$ (C1)

where $A_{irr}$ is the irrigated area ($km^2$), $IWR$ is the irrigation water requirement (mm/day), and $Es$ is the irrigation efficiency (%). The $IWR$ can be calculated based on the continuity equation in paddy fields (Kang & Park, 2014; Song, Her, Jun, et al., 2019):

$$\frac{dPD}{dt} = RAIN + IWR - (DR + ET + INF)$$ (C2)

where $PD$ is the ponding depth (mm/day), $RAIN$ is the rainfall on paddy fields (mm/day), $DR$ is the surface drainage (mm/day), $ET$ is the actual evapotranspiration (mm/day), and $INF$ is the infiltration (mm/day). $ET$ is calculated by multiplying the reference evapotranspiration by the crop coefficient. We used the Food and Agriculture Organization (FAO) Penman-Monteith equation (Allen et al., 1998) to estimate the reference evapotranspiration and adopted the crop coefficient (Figure C1) for a Korean rice paddy (Yoo et al., 2013). $DR$ occurs when the $PD$ is greater than the height of the outlet weir ($LH$, Figure C1) (Kang & Park, 2014; Song, Her, Jun, et al., 2019):

$$DR = \begin{cases} 
PD - LH, & PD > LH \\
0, & \text{otherwise}
\end{cases}$$ (C3)

The $IWR$ can be calculated by subtracting $PD$ from the recommended ponding depth ($PDrec$, Figure C1) when $PD$ drops below $PDrec$ (Kang & Park, 2014; Khepar et al., 2000; Song, Her, Jun, et al., 2019):

![Figure C1. Seasonal variations of regionalized outlet height ($LH$), recommended ponding depth ($PDrec$), and crop coefficients ($Kc$) in Korean paddy fields.](image-url)
\[ S_{PS}, S > S_{PS} \text{ and } PS \leq PS_{\text{max}} \]
\[ PS_{\text{max}}, S > S_{PS} \text{ and } PS > PS_{\text{max}} \]  
\[ S_{ES}, S > S_{ES} \text{ and } ES \leq ES_{\text{max}} \]
\[ ES_{\text{max}}, S > S_{ES} \text{ and } ES > ES_{\text{max}} \]  

where \( S_{PS} \) and \( S_{ES} \) are the reservoir storage corresponding to the flood-limited level and the normal pool level (m), respectively, and \( PS_{\text{max}} \) and \( ES_{\text{max}} \) are the maximum principal spillway release and emergency spillway release (m\(^3\)/s).

### D. Performance Statistics

Equations, ranges, and optimal values of performance statistics used in this study appear in Table D1.

### E. Multi-Objective Optimization

In the parameter calibration, a sampling-based heuristic optimization algorithm called the Non-Dominated Sorting Genetic Algorithm II (NSGA-II; Deb et al., 2002) was employed to find a Pareto set that satisfies multiple objectives (\( E_{NS} \) and \( E_{NS,\text{log}} \)). NSGA-II is capable of handling objective functions without the need for weighting or combining objective functions, and it has been widely applied for hydrological modeling (Bekele & Nicklow, 2007; Ercan & Goodall, 2016; Khu & Madsen, 2005; Zhang et al., 2017). This algorithm employs a fast, non-dominating sorting approach to discriminate solutions based on the concept of Pareto dominance and optimality (Deb et al., 2002).
F. A Showcase of the Proposed Framework

Figure F1 illustrates how expert knowledge about reservoir operations combined with hydrological reasoning (reservoir water balance) and supplementary observations (reservoir water levels) can construct a full picture of reservoir hydrology, including mass curves and flow duration curves.

Figure F1. Examples demonstrating how the proposed framework can be used to construct a full picture of reservoir hydrology (using the example of the Idong reservoir).
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Data Availability Statement

Data in this study can be accessed from the repository: WRR_2020WR028183. https://doi.org/10.17655/OSF.IO/PM2NW.
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