

Research Article

Flood Impact Assessment, LSTM-Based Forecasting, and Revenue Loss Analysis of the Melamchi Water Supply Project

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Abstract

The Melamchi Water Supply Project (MWSP) was launched to address water shortages in Kathmandu Valley but faced significant disruptions due to the catastrophic floods of June 2021. These floods caused 503 non-functional days and revenue losses of NRs. 823.10 million, underscoring systemic vulnerabilities, inadequate disaster preparedness, and insufficient contingency planning. This study evaluates MWSP's performance by analyzing water discharge trends, forecasting missing data, and estimating financial impacts. A Long Short-Term Memory (LSTM) model was employed to predict water discharge using the recorded data at Sundarijal Treatment Plant by Kathmandu Upatyaka Khanepani Limited (KUKL), achieving a Mean Absolute Percentage Error (MAPE) of 6.82% and a coefficient of determination (R^2) of 0.63. However, the model struggled with abrupt changes caused by disasters, leaving 37% of variance unexplained. The findings highlight the need for enhanced disaster resilience, diversified water supply strategies, proactive maintenance, and hybrid forecasting models that integrate machine learning with domain-specific knowledge and external variables. These measures can improve MWSP's reliability and sustainability, ensuring consistent water supply amidst urbanization and climate-induced risks. This research provides actionable insights for stakeholders to strengthen water management frameworks and support Kathmandu Valley's long-term water security.

Keywords

LSTM, Revenue Loss, Missing Discharge, Debris Flow, MWSP

1. Introduction

Nepal is south Asian landlocked nation featured by difficult topography, different climatic conditions, complex geological structures and regular seismic activities. Hilly and moun-

tainous region cover about 87% of the total land area of Nepal and elevation varies from 59 m. in Terai in south to 8848 m in about 200 KM horizontal stretch [1]. This variation within a

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short distance makes country vulnerable to various water-induced natural disasters like landslides, slope failures, soil erosion, and debris flows [2].

Nepal has been experiencing different types of natural hazard in recent years. Nepal ranks at 20th position in multi hazard prone countries in the world [3]. According to [4], the nation also ranked at 4th, 11th, and 30th in terms of climate change, earthquakes, and flood risk respectively. Landslides, fires, droughts, epidemics, storms, hailstorms, avalanches, and Glacier Lake outburst floods are the recurrent natural incident frequently occurring in country. The number of natural calamities and number of deaths, injury, and economic loss is substantially escalating over the years [5].

To address the ongoing water shortage in the Kathmandu Valley, the government launched the Melamchi Water Supply Project (MWSP) in 2000. The project aimed to transport 170 million liters of fresh water daily from the Melamchi River to the valley through a 26-kilometer-long tunnel. However, the project faced numerous challenges, including delays, corruption, poor management, lack of teamwork, and insufficient technical expertise [6]. After two decades of struggles and uncertainties, the project was finally inaugurated in April 2021. Unfortunately, just two and a half months later, in June 2021, severe flooding and debris flow damaged critical parts of the project, including the headworks, the nearly completed Ambathan tunnel, roads, and bridges. As a result, water supply to the Kathmandu Valley was disrupted for 503 days, from June 15, 2021, to December 8, 2022. Initial estimates by the project team revealed that the flooding caused damages amounting to approximately Rs 1.88 billion [6-9].

The first disaster on June 15 caused widespread destruction, claiming lives, destroying homes, and damaging critical infrastructure like the Melamchi Water Supply Project (MWSP), which provides drinking water to Kathmandu [9-11].

This research tries to fill the void by computing missing discharge and revenue loss by using machine learning.

2. Material and Methodology

The methodology section outlines the systematic approach adopted to analyze water discharge trends, forecast missing data, and estimate revenue losses for the Melamchi Water Supply Project (MWSP). The study integrates advanced machine learning techniques with robust statistical methods to ensure accurate and reliable results. Below, we detail the key steps of the methodology, including data preprocessing, outlier removal, model selection, hyperparameter configuration, and performance evaluation.

2.1. Sampling Design and Justification

The sampling design for this study was strategically developed to address the primary objective of evaluating the performance and operational challenges of the Melamchi Water Supply Project (MWSP), with a particular focus on

quantifying revenue losses during non-functional phases caused by natural disasters such as floods. The dataset used in this study comprises daily water discharge records collected at the Sundarijal Treatment Plant, which serves as the outlet for the tunnel transporting water from the Melamchi River to Kathmandu Valley. This location was chosen because it provides a centralized and reliable source of data that directly reflects the volume of water delivered to the end users. The temporal coverage spans from March 2021 to June 2023, encompassing both functional and non-functional phases of MWSP, including the catastrophic floods of June 2021 that severely disrupted operations. By analyzing discharge data from this critical endpoint, we ensure that the findings accurately represent the actual water supply trends and enable precise estimation of revenue losses based on KUKL's minimum tariff rate. Furthermore, the granularity of the dataset allows for robust preprocessing and modeling using advanced machine learning techniques, such as Long Short-Term Memory (LSTM) models, to forecast missing discharge values and assess system performance. This sampling approach not only aligns with the research objectives but also ensures the reliability and relevance of the analysis, providing actionable insights for improving MWSP's resilience and sustainability.

2.2. Data Collection and Preprocessing

The dataset used in this study was obtained from the Sundarijal Treatment Plant, managed by Kathmandu Upatyaka Khanepani Limited (KUKL). It consists of daily water discharge records (in cubic meters) spanning from March 2021 to June 2023. These records were collected during both operational and non-functional phases of the Melamchi Water Supply Project (MWSP), including periods of disruption caused by natural disasters such as floods and infrastructure failures.

Raw datasets often contain anomalies or outliers that can distort analysis and forecasting accuracy. To ensure data reliability, a robust preprocessing step was implemented. Outliers were identified and removed using the Modified Z-Score method, a statistical technique that evaluates how far each data point deviates from the median in terms of the Median Absolute Deviation (MAD). A threshold of 3.5 was applied to flag and exclude outliers, ensuring the dataset remained representative while minimizing noise [12-14]. This approach is particularly effective for hydrological data, which often exhibits skewness and extreme values due to seasonal variations and unforeseen events like floods.

The preprocessing step not only improved the consistency of the dataset but also enhanced the model's ability to capture underlying trends. Care was taken to ensure that critical extreme events, such as flood-related disruptions, were not inadvertently excluded during outlier removal. The filtered dataset provided a more reliable foundation for further analysis, enabling accurate forecasting of missing water discharge

values and supporting informed decision-making for sustainable water resource management.

Figure 2 illustrates the impact of outlier removal on the dataset, highlighting the transition from highly variable raw data to a more consistent and interpretable filtered dataset. This refined dataset serves as the basis for training and testing the LSTM model, ensuring robust performance and meaningful insights into MWSP's operational challenges.

2.3. Model Selection: Justification for LSTM

The choice of the Long Short-Term Memory (LSTM) model for forecasting water discharge was driven by its proven ability to handle complex, nonlinear, and sequential data patterns characteristic of hydrological systems. Unlike traditional statistical models such as ARIMA, which are limited to linear relationships and stationary data, LSTMs excel at capturing long-term dependencies and temporal dynamics in time-series data [15]. This capability is essential for modeling water discharge influenced by seasonal variations, operational disruptions, and extreme events like floods.

Several studies have demonstrated the effectiveness of LSTMs in hydrological forecasting. For instance, [14] successfully applied LSTM for operational low-flow forecasting, highlighting its ability to model intricate hydrological patterns with high accuracy. Similarly, [16] utilized LSTM to enhance river streamflow forecasts across the western United States, achieving superior performance compared to conventional methods. [17] also applied LSTM for flood forecasting, underscoring its robustness in handling abrupt changes caused by natural disasters.

Compared to alternative recurrent neural networks (RNNs) like Gated Recurrent Units (GRUs), LSTMs offer a more sophisticated architecture with memory cells and gating mechanisms that enable better retention of critical information over extended periods [18]. This capability is essential for accurately predicting water discharge trends in MWSP, where historical observations and external meteorological variables significantly influence future outcomes.

A comparative analysis of LSTM, ARIMA, and GRU highlights distinct advantages of LSTM for this application. While ARIMA is computationally efficient and suitable for short-term linear predictions, it struggles with nonlinearities and long-term dependencies inherent in hydrological data. GRUs, though similar to LSTMs in their ability to model sequential data, often underperform in scenarios requiring prolonged memory retention due to their simplified architecture. In contrast, LSTM's ability to balance complexity and accuracy makes it the most appropriate model for capturing both short-term fluctuations and long-term trends in MWSP's water discharge data [19, 20].

2.4. LSTM Model Configuration

To ensure the reliability and accuracy of the LSTM model,

careful consideration was given to the selection of hyperparameters. The following configurations were implemented:

a) Number of Layers:

A single-layer LSTM was chosen based on computational constraints and the complexity of the dataset. While multi-layer LSTMs can capture more intricate patterns, they often require significantly more computational resources and are prone to overfitting when applied to smaller datasets. Literature such as [16] suggests that single-layer LSTMs are sufficient for many hydrological applications, provided the dataset is adequately preprocessed.

b) Number of Epochs and Early Stopping:

The model was trained for a maximum of 100 epochs, with early stopping implemented to prevent overfitting. Early stopping monitors the validation loss and halts training when no improvement is observed for 10 consecutive epochs. This approach ensures that the model generalizes well to unseen data while minimizing computational costs [14].

c) Batch Size:

A batch size of 1 was selected based on trial-and-error experiments and recommendations from similar studies. Smaller batch sizes improve model convergence but increase training time, while larger batch sizes reduce training time but may lead to suboptimal solutions. A batch size of 1 strikes a balance between computational efficiency and model performance [17].

d) Learning Rate and Optimization Algorithm:

The Adam optimizer was used with a default learning rate of 0.001, a widely adopted choice in deep learning due to its adaptive learning rate capabilities and robust performance across various tasks. The learning rate was fine-tuned using a grid search to ensure optimal convergence [21].

e) Activation Functions:

The activation function for the LSTM layers was set to tanh, which is the default choice for LSTMs due to its ability to handle vanishing gradient problems effectively. The output layer used a linear activation function to predict continuous water discharge values [22].

f) Hyperparameter Tuning:

Hyperparameter tuning was performed using a grid search to evaluate combinations of learning rates, batch sizes, and numbers of epochs. The combination that yielded the lowest validation error was selected for the final model [23].

2.5. Performance Evaluation

The performance of the LSTM model was evaluated using two key metrics, Mean Absolute Percentage Error (MAPE) and the Coefficient of Determination (R^2). These metrics provide insights into the accuracy and explanatory power of the model. The MAPE measures the average percentage deviation of predicted values from actual values, while R^2 quantifies the proportion of variance explained by the model [14]. These metrics provided insights into how well the model captured the underlying patterns in the data and the magnitude

of errors in its predictions.

2.6. Revenue Loss Analysis

Once the missing water supply data was forecasted using the LSTM model, the reconstructed dataset was used to es-

timate the potential revenue loss caused by the disruption. For this calculation, we considered the minimum tariff rate set by KUKL for household connection through half inch pipe of NRs. 100 per 10000 Liters of water. Detailed tariff is as explained in following Table 1 [24].

Table 1. KUKL Tariff Rate 2013.

Connection Pipe Size	Minimum Water Consumed (Liter)	Minimum Tariff Rate NRs.	Rate for Additional Water above Minimum Water Consumed (per 1000 Liters) NRs.
½ inch	10000	100	32
¾ inch	27000	1910	71
1 inch	56000	3960	71
1.5 inch	155000	10950	71
2 inches	320000	22600	71
3 inches	881000	62240	71
4 inches	1810000	127865	71

3. Findings

3.1. Study of Water Supply Trend

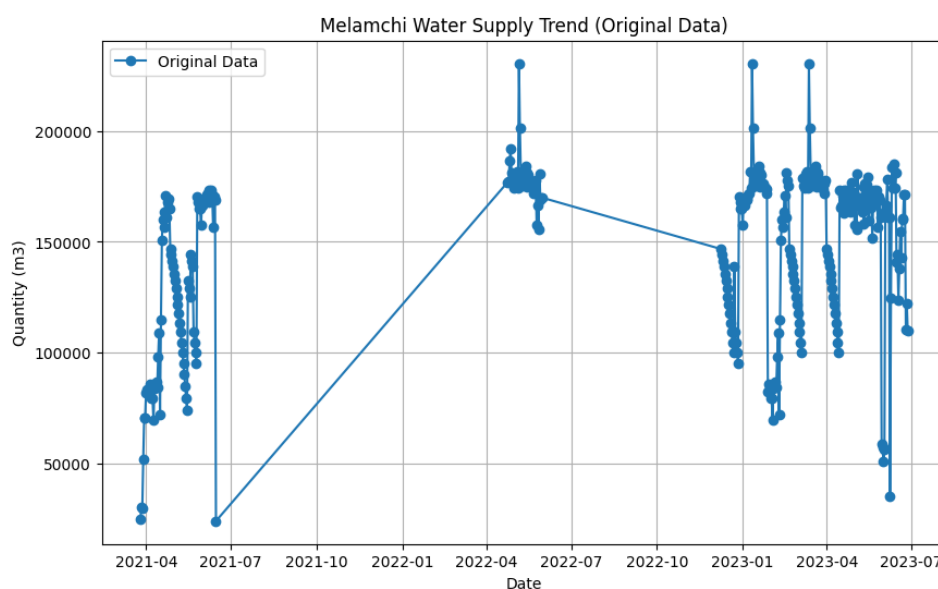


Figure 1. Original Water Supply Trend in Melamchi Water Supply as recorded in Sundarijal treatment Plant.

The Figure 1 reveals the trend of water supply from the Melamchi Water Supply Project to the Sundarijal Treatment Plant, showing both periods of functionality and significant disruptions. The blue dots on the graph represent when water was successfully delivered, with the height of each dot indi-

cating the volume of water supplied. These dots show that water flow initially surged in mid-2021. However, this was followed by a highly inconsistent trend, with frequent gaps where no water flowed at all—represented by the straight lines between the dots. These interruptions were largely caused by

the devastating floods of June 2021, which severely damaged the Melamchi River infrastructure, including critical components like the headworks and tunnels. Over time, the trend shows a worrying decline in water supply. After the initial surge, the flow became erratic, with sharp drops and prolonged periods of no discharge. By late 2022 and into 2023, the water

supply had dwindled significantly. This downward trend highlights the project's vulnerability to natural disasters like floods, as well as ongoing operational and maintenance challenges. The findings emphasize that while the project showed promise initially, its inability to maintain a consistent water supply has left Kathmandu facing continued water shortages.

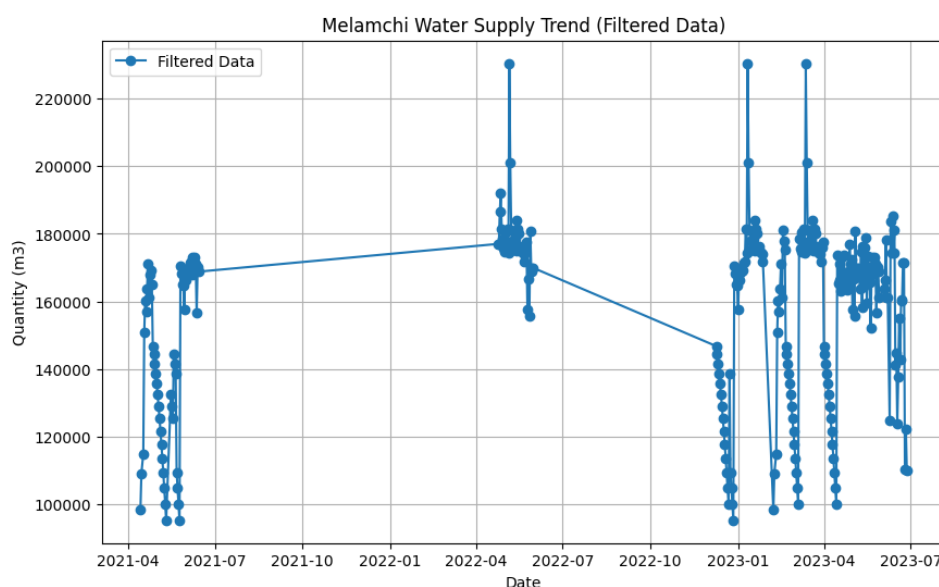


Figure 2. Filtered Data After Removing Outliers from the Original Data.

The analysis of water discharge data from the Melamchi Water Supply Project utilized the Modified Z-Score method to filter outliers and reveal underlying trends as shown in Figure 2. The original dataset exhibited significant variability, with extreme values likely caused by operational disruptions, natural events like floods, or measurement errors. To address this, the Modified Z-Score, a robust statistical approach based on the median and Median Absolute Deviation (MAD) was applied to each data point. A threshold of 3.5 was used to

identify and remove outliers, resulting in a filtered dataset that eliminated anomalies while retaining representative values. The filtered data demonstrated a more consistent trend, with a narrower range, reduced variability, and a median stabilized around 140,000 m³. This process highlights the critical role of outlier removal in hydrological data analysis, enabling a clearer understanding of typical water supply patterns and supporting informed decision-making for sustainable water resource management.

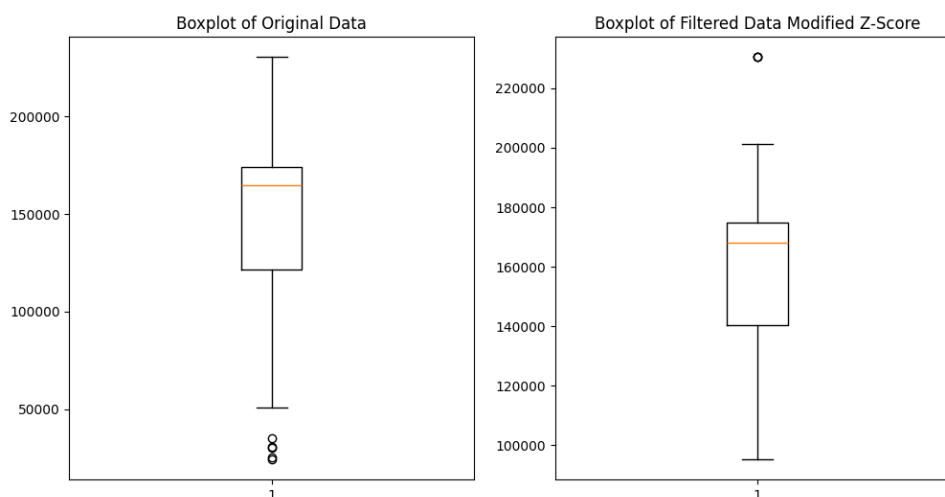


Figure 3. Boxplot of water discharge data before and after outlier removal using the Modified Z-Score method.

The Figure 3 illustrates the water discharge trend from April 2021 to July 2023 after filtering outliers using the Modified Z-Score method, providing a more reliable dataset for analysis. The filtered data reveals an initial surge in discharge to over 200,000 m³ by June 2021, likely due to seasonal rains or the system reaching full operational capacity, followed by significant fluctuations and a gradual decline to around 100,000-120,000 m³ by mid-2023. By removing ex-

treme values caused by anomalies such as floods or operational disruptions, the filtering process highlights underlying trends, including the project's struggles with consistency, potentially due to infrastructure damage from the 2021 floods. This refined dataset is critical for further analysis, as it serves as the foundation for predicting missing discharge values using LSTM method.

3.2. Summary of Water Supply in MWSP

Table 2. Status of Melamchi Water Supply.

S.N.	Start Date	End Date	Remarks
1	26 th March 2021	14 th June 2021	MWSP Functional Phase
2	15 th June 2021	23 rd April 2022	MSWP non-functional First Phase
3	24 th April 2022	31 st May 2022	MWSP functional Phase
4	1 st June 2022	8 th December 2022	MSWP non-functional Second Phase
5	9 th December 2022	27 th June 2023	MWSP functional Phase

The Table 2 outlines the functional and non-functional periods of the Melamchi Water Supply Project (MWSP) from March 2021 to June 2023, revealing a pattern of intermittent functionality. MWSP was operational for short periods, such as from March to June 2021, April to May 2022, and December 2022 to June 2023, with the longest continuous operation being the final stretch of six and a half months. However, these operational phases were interrupted by extended non-functional periods, including a 10-month shutdown from June 2021 to April 2022 following severe flooding that damaged critical infrastructure. The frequent alternations between operation and downtime highlight the

project's vulnerability to natural disasters and technical challenges, emphasizing the need for improved disaster resilience and maintenance strategies to ensure consistent water supply to Kathmandu Valley.

3.3. Forecasting of Missing Data

The two Figures 4 and 5 provide critical insights into the performance and limitations of the LSTM model in forecasting water discharge for the Melamchi Water Supply Project, while also highlighting the broader implications of using filtered data for such analyses.

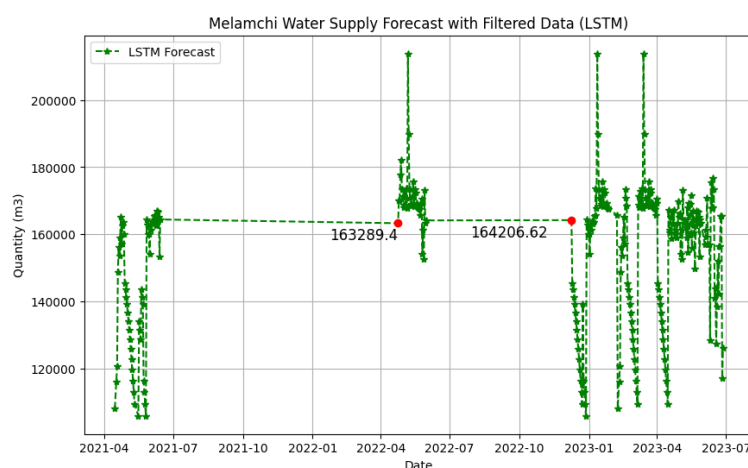


Figure 4. Forecasted water discharge values generated by the LSTM model based on filtered data.

Figure 4, presents the forecasted water discharge values generated by the model over the period from April 2021 to July 2023. The X-axis represents the timeline, while the Y-axis measures water discharge in cubic meters (m^3), ranging from approximately 100,000 m^3 to 200,000 m^3 . The green dots represent the forecasted values, connected by dashed lines to illustrate trends, with a solid green line providing a smoothed representation of the overall forecast. Specific historical data points, marked with red circles, showed that the

forecasted missing discharge, for the first phase of non-functionality of MWSP 163,289.4 m^3 was forecasted and 164,206.62 m^3 was forecasted in second phase of non-functionality of MWSP. The forecast captures fluctuations in water discharge, reflecting operational challenge caused by Melamchi flood of 2021. Despite these challenges, the model predicts both short-term fluctuations and long-term stabilization, indicating gradual improvements in the system's resilience.

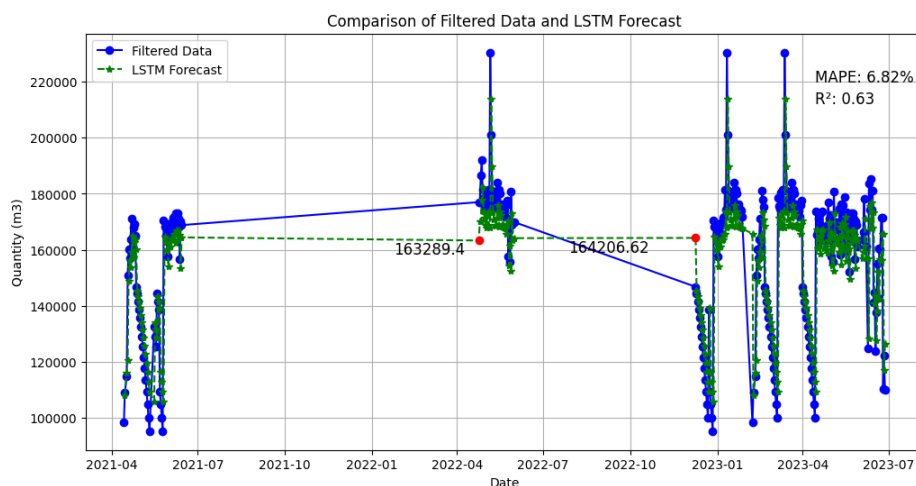


Figure 5. Comparison of filtered water discharge data (blue) and LSTM forecast (green). Performance metrics: MAPE = 6.82%, $R^2 = 0.63$.

Figure 5 provides a direct comparison between the filtered data and the LSTM forecast, offering a quantitative assessment of the model's accuracy. The blue dots and line represent the filtered data, which smooths out extreme fluctuations by removing outliers, while the green dots and line depict the forecasted values. Two key performance metrics Mean Absolute Percentage Error (MAPE) is 6.82%, indicating that the forecast deviates from the actual values by an average of

6.82%, demonstrating high accuracy. The Coefficient of Determination (R^2) is 0.63, suggesting that the model explains approximately 63% of the variance in the filtered data. While this indicates a strong correlation, it also highlights opportunities for further refinement to capture additional variability. Together, these figures underscore the LSTM model's ability to handle complex, intermittent patterns in water discharge, making it a valuable tool for predicting future trends.

3.4. Revenue Loss in MWSP

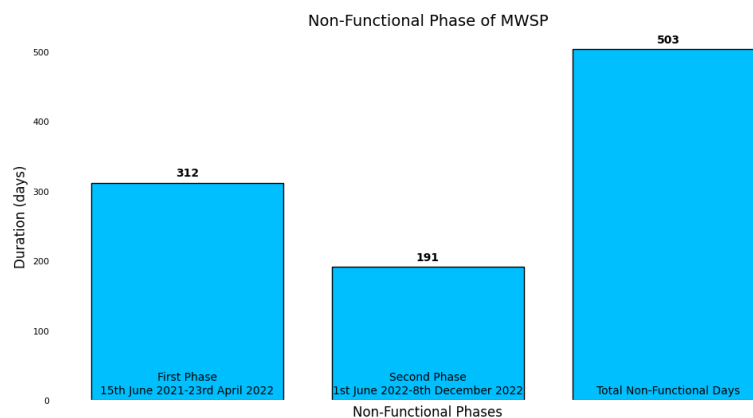


Figure 6. Non-Functional Phase of MWSP.

Figure 6 analyzing the non-functional phases of the MWSP reveals significant operational disruptions, with a cumulative total of 503 non-functional days over two years, from June 2021 to December 2022. The first phase, lasting 312 days from June 2021 to April 2022, was primarily attributed to the catastrophic floods of June 2021, which caused extensive damage to critical infrastructure such as headworks, tunnels, and approach roads [25]. The second phase, spanning 191 days from June 2022 to December 2022, highlights ongoing challenges, likely stemming from residual damage, inadequate maintenance, or emerging operational inefficiencies.

These prolonged periods of non-functionality underscore the project's vulnerability to natural disasters and systemic issues, significantly impacting water supply reliability in Kathmandu Valley. The findings emphasize the urgent need for enhanced disaster resilience, proactive maintenance strategies, and robust contingency planning to mitigate the impact of future disruptions and ensure sustainable water resource management. Such measures are critical to reducing the frequency and duration of non-functional phases and improving the overall performance of the MWSP.

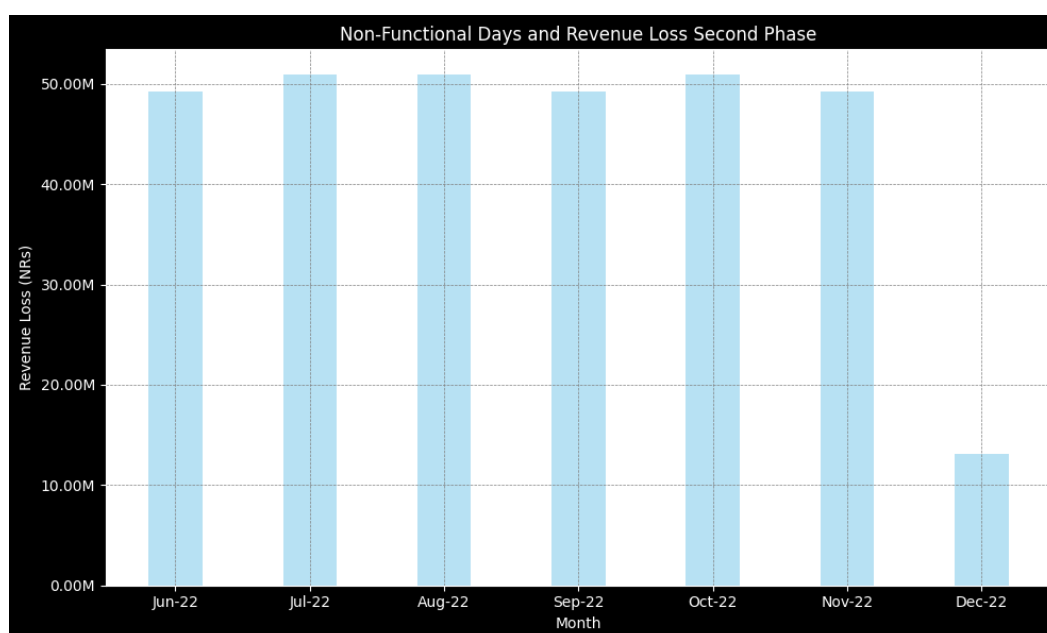


Figure 7. Revenue loss during the second non-functional phase (June 2022-December 2022).

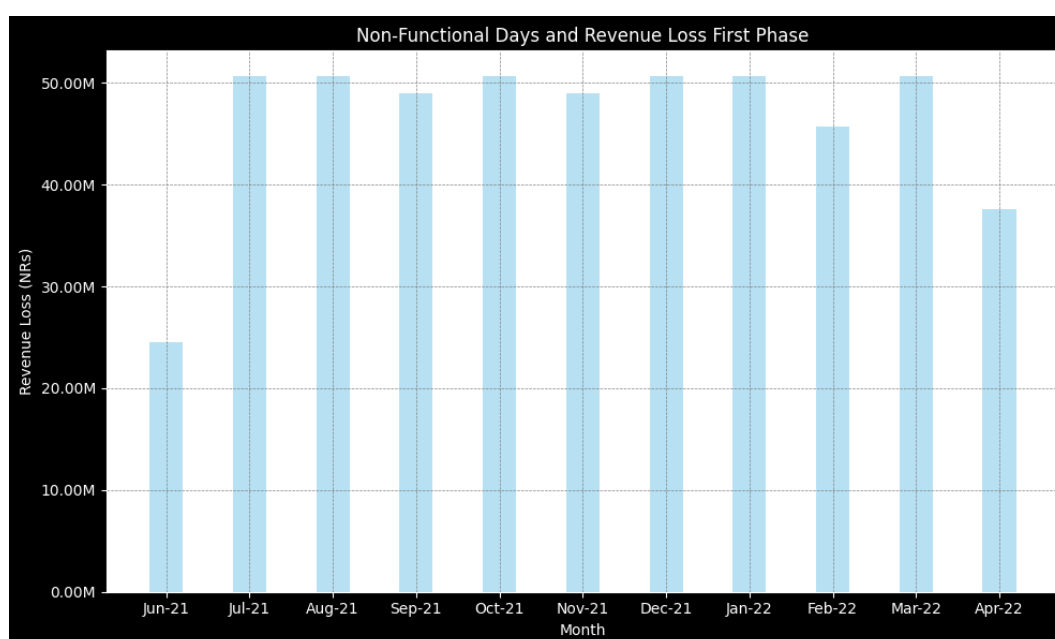


Figure 8. Revenue loss during the first non-functional phase (June 2021-April 2022).

The analysis of revenue loss for the Melamchi Water Supply Project (MWSP) during its non-functional phases reveals significant financial implications for Kathmandu Upatyaka Khanepani Limited (KUKL), calculated using the minimum tariff rate of NRs. 100 per 10,000 liters of water [26]. On a monthly basis as shown in Figure 8, the losses ranged from NRs. 24,493,410 in June 2021 (15 non-functional days) to NRs. 50,619,714 in months with 31 non-functional days, such as July, August, and October 2021. The cumulative revenue loss over the first phase (June 2021 to April 2022) amounts to NRs. 509.46 million, representing the minimum estimated financial impact since the calculation is based on the lowest tariff rate. Critically, this figure likely underestimates the true economic burden, as it does not account for potential additional costs such as emergency water sourcing, groundwater extraction, or reputational damage due to service interruptions. Furthermore, the reliance on MWSP as a primary water source highlights KUKL's vulnerability to systemic disruptions, which are exacerbated by natural disasters like the June 2021 floods. These prolonged non-functional phases not only strain KUKL's financial stability but also hinder its ability to invest in infrastructure improvements or customer service enhancements, creating a ripple effect of inefficiency. The findings underscore the urgent need for KUKL to adopt a more resilient operational framework, including diversified water supply strategies, proactive maintenance, and contingency planning, to mitigate future revenue losses.

The second phase of non-functional of MWSP, spanning from June 2022 to December 2022, critically underscores the systemic vulnerabilities and financial strain imposed on Kathmandu Upatyaka Khanepani Limited (KUKL) due to prolonged operational disruptions. This phase is a direct aftermath of the catastrophic floods of June 2021, which severely damaged critical infrastructure, including headworks, tunnels, and approach roads. The data reveals that MWSP was non-functional for 30 or 31 days in most months from June to November 2022, leading to staggering monthly revenue losses ranging between NRs. 49.3 million and NRs. 50.9 million as shown in Figure 7, calculated using the minimum tariff rate of NRs. 100 per 10,000 liters of water. These figures likely underestimate the true economic impact, as they exclude additional costs such as emergency water sourcing, groundwater extraction, or infrastructure repairs. The cumulative revenue loss for this period amounts to NRs. 313.6 million, highlighting the severe financial burden on KUKL and its inability to meet Kathmandu Valley's water demands consistently. Critically, the persistence of high losses over six months reflects not only the lingering effects of the 2021 floods but also systemic inefficiencies, inadequate maintenance, and insufficient contingency planning. While December 2022 shows a sharp decline in non-functional days to just 8 days, resulting in a reduced revenue loss of NRs. 13.1 million, this improvement comes nearly 1.5 years after the initial disaster, raising concerns about the slow pace of re-

covery and the lack of proactive measures to mitigate such disruptions. This delay underscores the urgent need for enhanced disaster resilience, diversified water supply strategies, and robust infrastructure management to ensure sustainable water resource delivery. Furthermore, the reliance on MWSP as a primary water source exposes KUKL's operational fragility, emphasizing the importance of investing in alternative water sources and redundancy systems to cushion against future shocks. Addressing these critical gaps is essential to safeguarding KUKL's financial stability and ensuring reliable water supply for Kathmandu Valley, particularly in the face of increasing climate-induced risks and growing urban water demands.

4. Conclusion

In conclusion, this research critically analyzes the performance and operational challenges of the Melamchi Water Supply Project (MWSP), focusing on its non-functional phases, financial implications, and predictive modeling for water discharge. The findings reveal that MWSP experienced significant disruptions totaling 503 non-functional days across two phases, primarily due to the catastrophic floods of June 2021, which severely damaged critical infrastructure such as headworks, tunnels, and approach roads. These disruptions resulted in substantial revenue losses amounting to approximately NRs. 823.10 million, calculated using the minimum tariff rate of NRs. 100 per 10,000 liters of water, though the true economic impact is likely higher when accounting for additional costs like emergency water sourcing and reputational damage. The persistence of high monthly losses, ranging from NRs. 49.3 million to NRs. 50.9 million, underscores the severe financial strain on Kathmandu Upatyaka Khanepani Limited (KUKL) and highlights systemic inefficiencies, inadequate disaster preparedness, and insufficient contingency planning. The LSTM model demonstrated reasonable accuracy in forecasting water discharge trends, with a MAPE of 6.82% and an R^2 value of 0.63, but struggled to account for abrupt changes caused by natural disasters or operational failures, leaving nearly 37% of the variance unexplained. This limitation emphasizes the need for hybrid modeling approaches that integrate machine learning with domain-specific knowledge, external variables, and real-time monitoring. Critically, the study exposes MWSP's vulnerability to climate-induced risks and operational disruptions, exacerbated by its reliance on a single water source and the slow recovery process spanning over 1.5 years. To address these challenges, stakeholders must adopt a multi-pronged approach, including strengthening disaster-resilient infrastructure, implementing proactive maintenance strategies, diversifying water supply sources, and advocating for policy reforms and increased funding. By addressing these gaps, stakeholders can enhance the resilience and reliability of MWSP, ensuring sustainable water supply for Kathmandu

Valley amidst growing urbanization and escalating climate risks. This research not only sheds light on MWSP's operational vulnerabilities but also provides actionable insights for building a more resilient and sustainable water management framework to meet the region's growing demands.

Abbreviations

KUKL	Kathmandu Upatyaka Khanepani Limited
LSTM	Long Short-Term Memory
MAD	Median Absolute Deviation
MAPE	Mean Absolute Percentage Error
MWSP	Melamchi Water Supply Project
NRs	Nepalese Rupees
R ²	Coefficient of Determination

Declaration

We declare that the manuscript titled "Flood Impact Assessment, LSTM-Based Forecasting, and Revenue Loss Analysis of the Melamchi Water Supply Project" is original and has not been published or submitted for publication elsewhere. The contributions of the authors are as follows: the first author developed the concept, developed model and drafting manuscript; the second author contributed to the concept development, data collection and manuscript drafting; the third author has supervised this project and drafting manuscript and fourth author was responsible for concept development and drafting the manuscript. All authors have approved the final version of the manuscript.

Author Contributions

Kamal Katwal: Conceptualization, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing

Bidur Kandel: Conceptualization, Data curation, Methodology, Writing – original draft, Writing – review & editing

Dinesh Sukamani: Methodology, Supervision, Writing – original draft, Writing – review & editing

Sudeep Thapa: Conceptualization, Methodology, Writing – original draft, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

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