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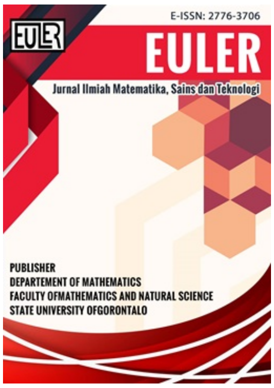

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Research Article

Spatial Planning of Mosque-Based Ablution Water Reuse Networks in Lombok Barat Using K-Means Clustering and Minimum Spanning Tree

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ABSTRACT. *Lombok Barat Regency, located on Lombok Island, frequently experiences water scarcity due to its semi-arid climate and prolonged dry seasons. Agricultural and plantation activities in this region rely heavily on limited freshwater resources, particularly in dryland areas. Meanwhile, mosques continuously generate relatively clean greywater from daily ablution (wudu) activities. Despite its regular availability and relatively low contamination level, this resource remains largely underutilized. This study examines the spatial planning of mosque-based wudu water collection networks in West Lombok as a potential supplementary water source for plantation and dryland irrigation. A spatial analytical framework combining K-Means clustering and the Minimum Spanning Tree (MST) algorithm was applied and implemented through an interactive RShiny application. Spatial data from 940 mosques were preprocessed and analyzed. K-Means clustering at Level 1 grouped mosques into 25 local service clusters, while Level 2 clustering aggregated these clusters into five main reservoir zones. A cost-weighted MST based on Haversine distance was then used to estimate the minimum pipeline length required to connect mosques within the proposed network configuration. The results show that the modeled network connects all 940 mosques with a minimum total pipeline length of 411,757.28 meters and could potentially collect approximately 282,000 liters of reusable wudu water per day. However, the model represents a preliminary spatial planning framework and does not include hydraulic simulations, water quality validation, treatment system design, or operational feasibility assessment.*

1. Introduction

Water scarcity has become a major environmental and socio-economic challenge in many parts of the world, particularly in semi-arid regions where agricultural production depends heavily on limited water resources. Effective water resource management is therefore essential to maintain agricultural sustainability and ecosystem stability. Previous studies on greywater treatment and reuse highlight the importance of alternative water resources in improving water-use efficiency [1]. In addition, modeling approaches have been developed to quantify environmental risks associated with water systems, including pathogen loads in water catchments [2]. The characteristics of greywater, including its relatively low contamination compared to blackwater, further support its potential for reuse in non-potable applications [3].

Various studies have also explored wastewater treatment technologies, including the removal of hazardous pollutants such as polychlorinated biphenyls (PCBs) [4], and the role of natural materials such as humic substances in reducing contaminant concentrations [5]. In the context of community health, access to safe water, sanitation, and hygiene services re-

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mains crucial, particularly in vulnerable communities [6]. More recent research emphasizes that greywater can be effectively treated and reused for various purposes, supported by appropriate technologies and user acceptance [7]. Furthermore, sustainability assessments of recycled water systems underline their potential contribution to long-term water resource management [8].

One potential and often overlooked source of greywater is ablution (wudu) water generated in mosques. In Muslim communities, mosques function as central religious facilities where ablution is performed several times daily before prayers, producing a continuous flow of greywater. Despite its availability, this water is generally discharged directly into drainage systems without reuse. Considering its relatively low pollutant content, ablution water represents a promising alternative water source that can be utilized after basic treatment, particularly for irrigation purposes.

The implementation of such reuse systems requires appropriate analytical and spatial planning approaches. Clustering techniques are widely used to identify spatial patterns and group similar data points. The K-Means algorithm, for example, has been applied in various studies, including tourism mapping [9], regional poverty classification [10], and infrastructure-based regional clustering [11]. In addition, clustering approaches combined with dimensionality reduction techniques such as Principal Component Analysis (PCA) have also been used to improve regional grouping accuracy in socio-economic studies [12].

In addition to clustering, optimization methods based on graph theory have been developed to improve network efficiency, such as the application of Minimum Spanning Tree (MST) algorithms for distribution network design [13]. The theoretical foundation of shortest path and network optimization can be traced back to Dijkstra's work on graph problems [14].

From a broader perspective, spatial planning and infrastructure development are closely related to urban science and geographic information systems (GIS). Concepts such as the science of cities [15], volunteered geographic information [16], and location science [17] provide a strong foundation for analyzing spatial data and supporting decision-making processes. Clustering itself has been extensively studied as a fundamental method in data analysis and pattern recognition [18], while decision-making frameworks such as multi-attribute decision making (MADM) support the evaluation of alternative planning strategies [19]. These analytical approaches are also relevant in engineering contexts, where systematic design and optimization are essential [20].

Despite these advancements, most existing studies on greywater reuse focus primarily on treatment technologies or small-scale household applications. Limited research has addressed the integration of spatial analysis and network optimization for designing community-based water reuse systems. In particular, the potential use of mosques as decentralized nodes for greywater collection and distribution has not been widely explored.

Therefore, this study proposes a spatial planning framework for mosque-based ablution water reuse networks in Lombok Barat using K-Means clustering and Minimum Spanning Tree algorithms. By utilizing spatial data from 940 mosques, this study aims to identify cluster structures and estimate the minimum connection distances required to develop an efficient water reuse network. The proposed framework is expected to support irrigation systems and contribute to sustainable water resource management in water-scarce regions.

2. Methods

2.1. Study Area and Data

This study focuses on the spatial distribution of mosques in Lombok Barat, Indonesia, which is located on the western part of Lombok Island in West Nusa Tenggara Province. West Lombok is characterized by a semi-arid climate with distinct dry seasons, where agricultural and plantation activities often experience water scarcity. The dataset consists of geographic coordinates representing mosque locations within Lombok Barat. The spatial data were obtained from publicly available geospatial sources, including *OpenStreetMap (OSM)* and supporting regional spatial datasets. The data were collected and compiled in 2024. Each mosque is represented as a spatial point defined by geographic coordinates (x_i, y_i), where x_i denotes longitude and y_i denotes latitude.

$$M = \{(x_i, y_i) \mid i = 1, 2, \dots, N\}, \tag{1}$$

where N represents the total number of mosques included in the dataset.

2.2. Data Preprocessing

Prior to analysis, the spatial dataset underwent several preprocessing and validation steps to ensure data quality and reproducibility. First, records with missing or invalid geographic coordinates were removed. Second, coordinate validation was conducted by verifying that all points fall within the administrative boundary of Lombok Barat. Third, duplicate entries were identified and removed by checking identical coordinate pairs. After preprocessing, the final dataset consisted of 940 valid mosque locations within Lombok Barat.

2.3. K-Means Clustering – Level 1

K-Means clustering is applied to group mosques into K_1 spatial clusters. The clustering objective is to minimize the average distance between mosques and their respective cluster centers:

$$\min \sum_{k=1}^{K_1} \sum_{(x_i,y_i)\in C_k} \|(x_i, y_i) - \mu_k\|, \tag{2}$$

where C_k is the set of mosques in cluster k, and $\mu_k = (\bar{x}_k, \bar{y}_k)$ is the centroid of cluster k. K-Means is widely used in spatial data analysis to identify geographic group structures and improve spatial resource allocation efficiency. Several studies in applied mathematical and spatial modeling have demonstrated its effectiveness for regional clustering and decision-support analysis [15–17].

The number of clusters K_1 was determined using the Elbow method, which evaluates the reduction in the within-cluster sum of squares (WCSS) as the number of clusters increases. The WCSS measures the compactness of clusters and is defined as:

$$\text{WCSS}(K) = \sum_{k=1}^{K_1} \sum_{(x_i,y_i)\in C_k} \|(x_i, y_i) - \mu_k\|^2, \tag{3}$$

where C_k represents the set of data points assigned to cluster k, μ_k denotes the centroid of cluster k, and K is the total number of clusters. As the number of clusters increases, the WCSS value decreases because data points become closer to their centroids. The optimal number of clusters is identified at the point where the rate of decrease in WCSS slows significantly, forming an “elbow” in the evaluation curve. Each Level 1 centroid represents a potential local wudu water collection point serving nearby mosques. The Elbow method is commonly used to determine the optimal number of clusters by examining the reduction in within-cluster variance and has been widely applied in clustering-based spatial studies and decision-support models [18].

2.4. K-Means Clustering – Level 2

K-Means Clustering – Level 2 identify larger water collection zones, the centroids from Level 1 are grouped into K_2 clusters using the same K-Means principle:

$$\min \sum_{j=1}^{K_2} \sum_{\mu_k \in D_j} \|\mu_k - v_j\|, \tag{4}$$

where D_j denotes the set of Level 1 centroids in cluster j, and v_j is the centroid of cluster j. The value of K_2 was selected based on cluster evaluation results and regional spatial distribution patterns, which indicate five major geographic zones across the study area that can function as main water aggregation reservoirs.

2.5. Distance Measurement

Distances between spatial points were calculated using the Haversine formula, which accounts for the curvature of the Earth and provides accurate measurements for geographic coordinates. For two spatial points i and j, the distance is expressed as:

$$d_{ij} = \text{Haversine}(i, j). \tag{5}$$

This distance metric is used as a proxy for the potential cost of pipeline construction between mosques.

2.6. Minimum Spanning Tree (MST)

The Minimum Spanning Tree (MST) algorithm determine the most efficient connection structure among mosques, the network is modeled as a weighted graph $G = (V, E)$, where nodes represent mosques and edge weights correspond to pairwise Haversine distances. The Minimum Spanning Tree (MST) algorithm is then applied to identify the set of edges that connects all nodes with the minimum total distance:

$$\min \sum_{(i,j) \in T} d_{ij}, \tag{6}$$

where T denotes the set of edges forming the spanning tree. The MST was constructed using Kruskal's algorithm, which iteratively selects the shortest available edge while preventing the formation of cycles until all nodes are connected. This procedure ensures a connected network with the smallest possible total pipeline length. Graph-based optimization methods such as the Minimum Spanning Tree are frequently applied in infrastructure network design to minimize connection distance while maintaining full connectivity among nodes. Previous studies in mathematical network analysis also demonstrate the applicability of MST for spatial connectivity problems and infrastructure optimization [19, 20].

2.7. Estimation of Reusable Wudu Water

The potential volume of reusable wudu water is estimated using a simplified linear model:

$$V = N \times v, \tag{7}$$

where V represents the total daily volume of reusable wudu water, N is the number of mosques, and v represents the estimated average daily wudu water production per mosque. The parameter v is derived from previous studies on ablution water generation in mosque facilities. This estimate provides an indicative measure of the potential water supply available for non-potable uses such as irrigation.

3. Results and Discussion

This section presents the results of spatial analysis and network modeling for mosque locations in Lombok Barat. The analysis follows the methodological stages described earlier. First, the spatial distribution of mosques, as defined in eq. (1), is examined after data preprocessing to ensure the dataset is valid for spatial modeling. Second, a two-level K-Means clustering procedure is applied to identify local mosque communities and broader spatial aggregation zones based on eq. (2), eq. (3), and eq. (4). Third, a Minimum Spanning Tree (MST) algorithm is used to estimate the most distance-efficient connection structure among mosque nodes using the formulation in eq. (6), with distances calculated using eq. (5). Finally, the potential volume of reusable wudu water is estimated using eq. (7) to illustrate the possible scale of water resources represented by the network.

3.1. Spatial Distribution and Preprocessing Results

This stage aims to validate the spatial dataset and identify the baseline distribution of mosques in West Lombok. The dataset, as formally defined in eq. (1), represents mosque locations using geographic coordinates. Data preprocessing was conducted by removing records with incomplete coordinates and duplicate entries to ensure spatial consistency before clustering and network analysis. The spatial distribution of mosques after preprocessing is illustrated in Figure 1.

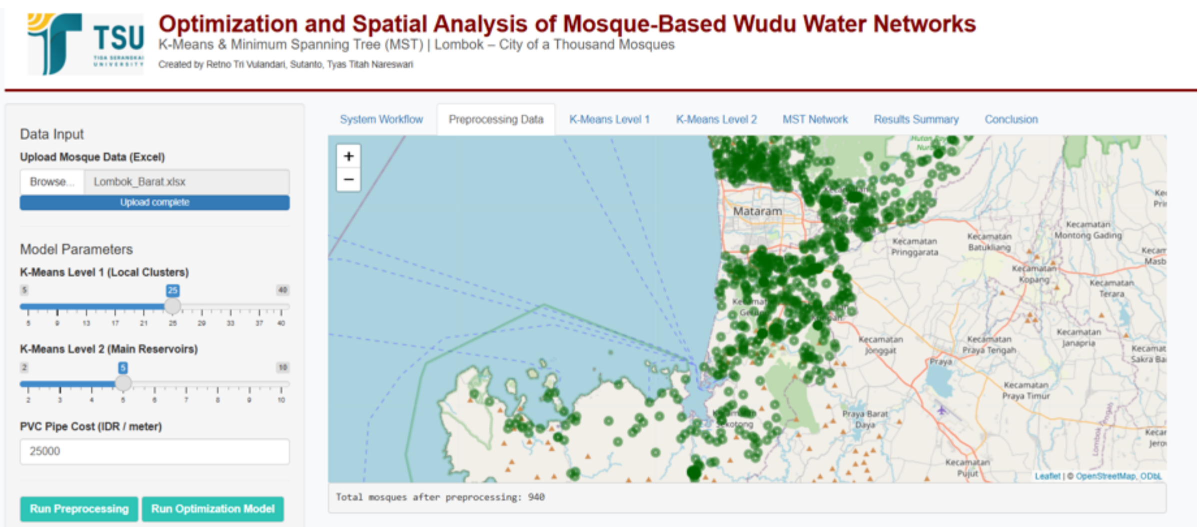

Figure 1. Spatial Distribution of Mosques in Lombok Barat

Figure 1 illustrates the spatial distribution of mosques in Lombok Barat after the preprocessing stage. A total of 940 mosque locations were retained for analysis after removing records with incomplete geographic coordinates and duplicate entries. The spatial distribution reveals heterogeneous density patterns across the region. Higher mosque concentrations appear in urban and peri-urban districts such as Gerung, Kediri, and Labuapi, whereas rural and plantation areas exhibit more dispersed spatial patterns. The average nearest-neighbor distance between mosques is approximately 420–460 meters, indicating relatively dense spatial infrastructure in populated areas. Such spatial proximity is advantageous for decentralized resource collection systems because shorter inter-mosque distances reduce potential pipeline requirements. Ensuring accurate geographic coordinates during preprocessing is therefore essential, as clustering and network optimization rely directly on spatial distance calculations. Overall, the validated dataset provides a consistent spatial representation of mosque infrastructure in West Lombok and forms the basis for subsequent clustering and network analysis.

3.2. K-Means Clustering Level 1: Local Wudu Water Communities

The objective of this stage is to identify local spatial groups of mosques as community-scale water collection units. K-Means clustering partitions the locations by minimizing within-cluster variance as defined in eq. (2), while the optimal number of clusters is determined using the WCSS formulation in eq. (3). This approach groups geographically proximate mosques into compact clusters that can share common water collection infrastructure. By reducing intra-cluster distances, it supports more efficient local distribution and collection. The results of the Level 1 clustering are illustrated in Figure 2.

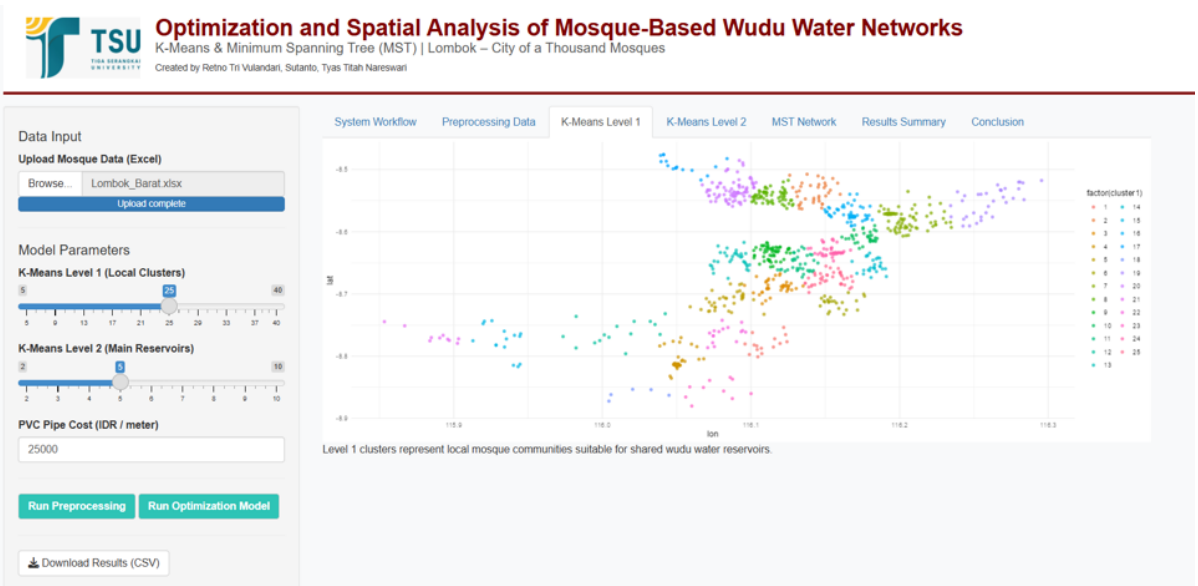

Figure 2. K-Means Level 1 Clustering

Figure 2 presents the results of Level 1 K-Means clustering, which grouped the 940 mosques into 25 spatial clusters. On average, each cluster contains approximately 37–38 mosques, although cluster sizes vary depending on local settlement density. Urban clusters contain a higher number of mosques within smaller spatial areas, while rural clusters cover larger geographic extents with fewer nodes. The clustering process minimizes within-cluster variance, resulting in compact spatial groupings. The average distance between mosques and their cluster centroid is estimated at approximately 1.2–1.5 km, indicating relatively localized service areas. This spatial structure suggests that Level 1 clusters could potentially function as community-scale water collection units, where mosques within the same cluster share a nearby collection point. From a network planning perspective, using 25 clusters provides a balance between spatial resolution and infrastructure complexity. A smaller number of clusters would significantly increase intra-cluster distances and pipeline requirements, whereas a larger number of clusters would require additional reservoirs and increase operational management complexity.

3.3. K-Means Clustering Level 2: Main Reservoir Aggregation

After identifying local clusters, the next step aims to group these clusters into broader spatial zones that may represent higher-level aggregation structures. The centroids obtained from Level 1 clustering are therefore used as input for a second K-Means clustering process based on eq. (4). This hierarchical clustering approach aggregates smaller spatial groups into larger zones, providing a simplified representation of regional spatial organization. This aggregation helps identify potential higher-level collection or storage locations that can serve multiple local clusters. The results of the Level 2 clustering process are illustrated in Figure 3.

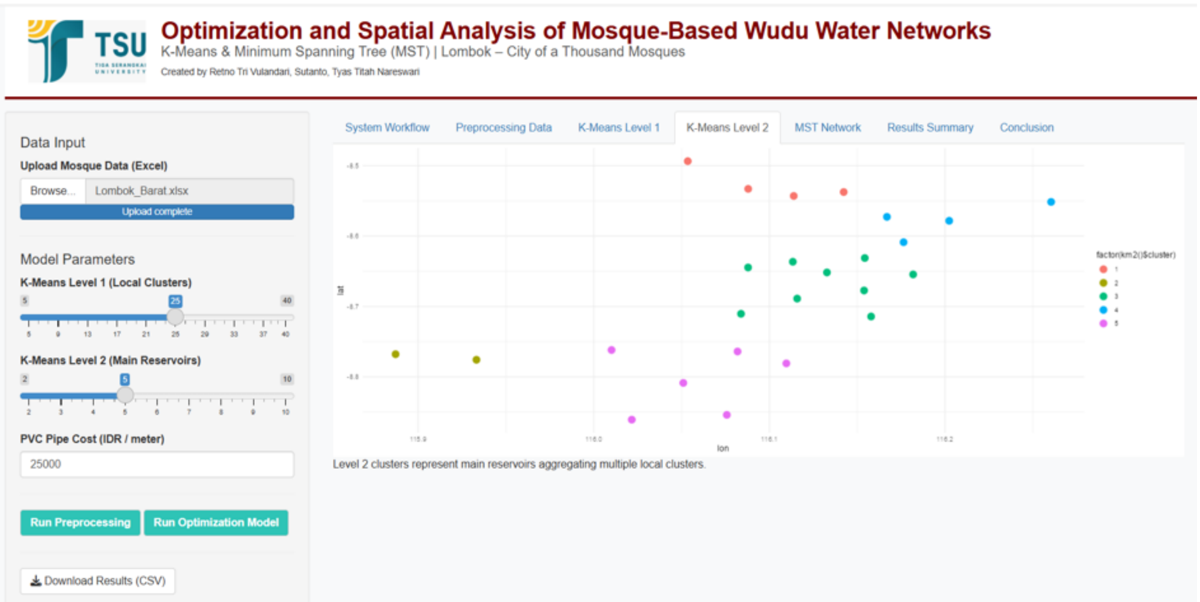

Figure 3. K-Means Level 2 Clustering

Figure 3 shows the results of Level 2 clustering, in which the 25 Level-1 centroids were grouped into five larger clusters. These clusters represent broader spatial zones that aggregate multiple local communities. Each Level-2 zone contains approximately 4–6 Level-1 clusters, depending on regional spatial distribution. The geographic configuration reflects the general settlement structure of West Lombok, where population centers and transportation corridors influence mosque density patterns. This hierarchical clustering structure provides a simplified spatial framework for organizing decentralized collection systems. By grouping smaller clusters into larger zones, the model illustrates how local collection points could theoretically be connected to higher-level storage facilities. However, this configuration should be interpreted primarily as a spatial grouping model, rather than a finalized infrastructure layout.

3.4. Minimum Spanning Tree (MST) Network and Infrastructure Optimization

This stage aims to estimate an efficient connection structure among mosque nodes based on geographic distance. Distances between spatial points are calculated using the Haversine formula as defined in eq. (5). The Minimum Spanning Tree (MST) algorithm is then applied to generate a network that connects all nodes while minimizing total connection length, following the formulation in eq. (6). The resulting network structure is illustrated in Figure 4.

Figure 4 illustrates the Minimum Spanning Tree (MST) network connecting all mosque nodes in West Lombok. The MST algorithm identifies the set of connections that links all nodes while minimizing the total connection distance. The resulting network produces a

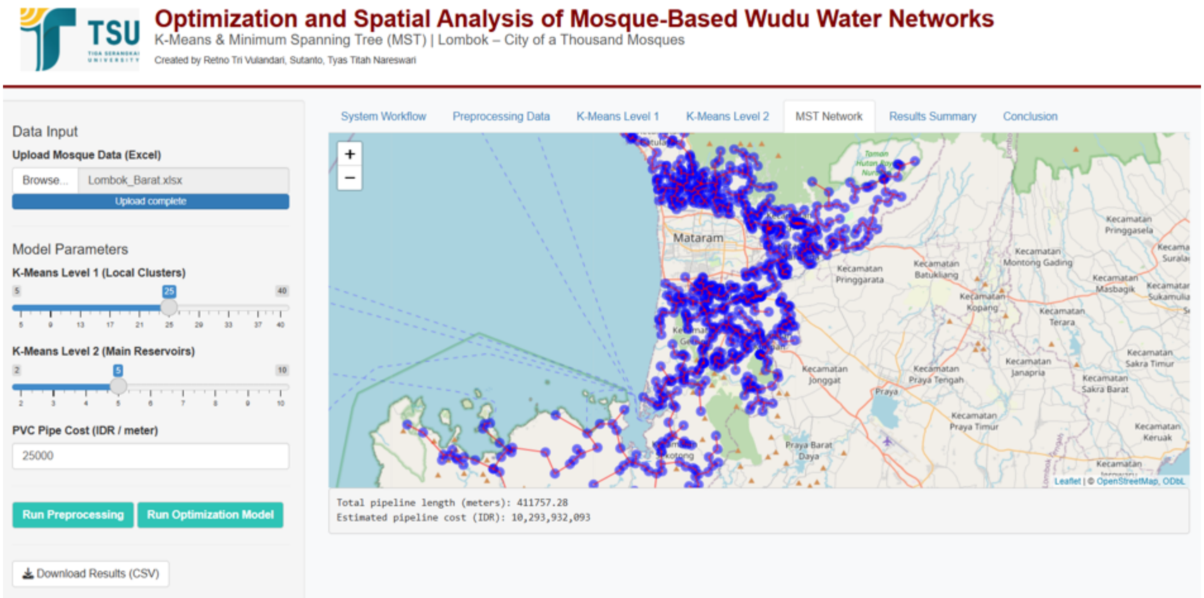

Figure 4. MST Network

minimum total connection length of 411,757.28 meters. This value represents the shortest theoretical pipeline length required to connect all nodes without forming redundant loops. Compared to arbitrary network connections, the MST structure reduces unnecessary pipeline duplication and provides an efficient baseline configuration. The MST network contains 939 edges, corresponding to the minimum number of connections required to link 940 nodes in a spanning tree structure. While this network minimizes total distance, it does not account for topographic constraints, land use barriers, hydraulic flow conditions, or construction feasibility. Therefore, the MST should be interpreted as a distance-based approximation of an efficient connection structure rather than a fully engineered pipeline design.

3.5. Potential Wudu Water Supply and Agricultural Implications

The final stage estimates the potential volume of reusable wudu water generated by mosques. This calculation is performed using the linear estimation model presented in eq. (7), which relates the total number of mosques to the average daily water production. The summary of the estimation results is illustrated in Figure 5.

Figure 5 summarizes the estimated water supply. Based on an estimated average production of 300 liters of wudu water per mosque per day, the system could potentially collect approximately 282,000 liters of reusable water per day across the study area. This estimate represents a theoretical aggregation of greywater generated from daily ablution activities. In practice, the usable volume would depend on several additional factors, including temporal variation in mosque attendance, water collection efficiency, treatment requirements, and storage capacity. Nevertheless, the estimated volume indicates that mosque-generated greywater may represent a locally available supplementary water resource. When combined with appropriate treatment systems, such water could potentially support non-potable applications such as landscape irrigation or certain agricultural uses.

3.6. Discussion and Policy Implications

The results demonstrate how spatial clustering and network analysis can be used to explore potential configurations of decentralized water collection systems. The combination of K-Means clustering and Minimum Spanning Tree analysis provides a systematic framework

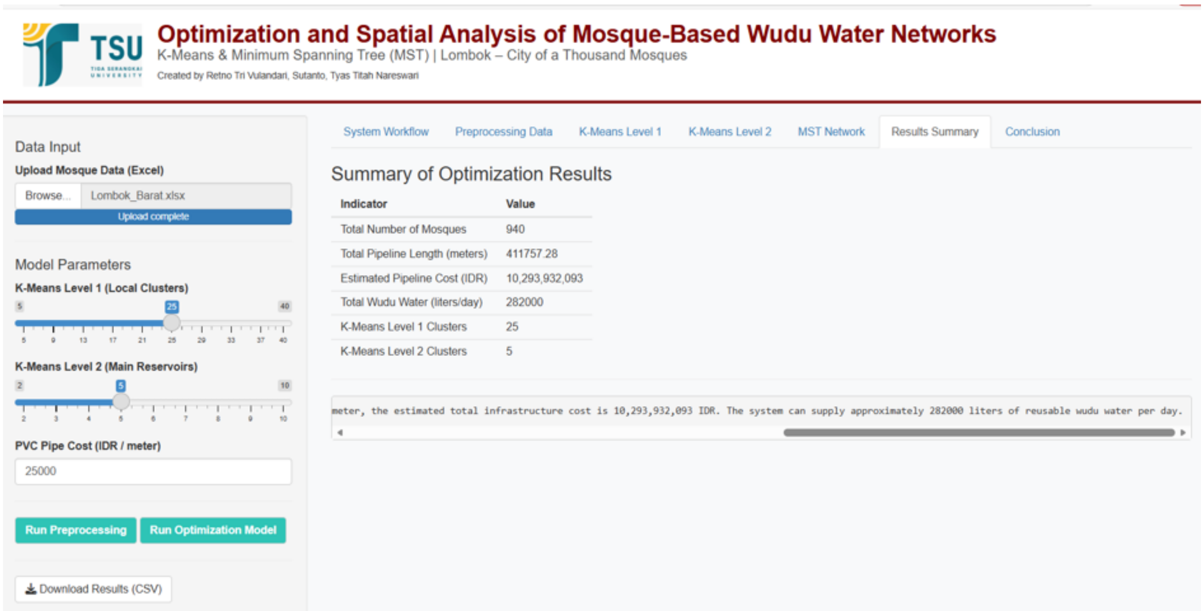

Figure 5. Results Summary

for identifying spatial groupings of mosques and estimating efficient connection structures. However, the results should be interpreted within the limitations of the current analytical framework. The proposed network configuration is based primarily on geographic coordinates and distance-based optimization. The analysis does not include hydraulic simulations, detailed infrastructure design, water treatment performance, land availability, or demand-location matching for irrigation systems. Consequently, the findings should be viewed as a preliminary spatial planning model that highlights the potential role of mosque infrastructure as decentralized water collection points. Further studies incorporating hydraulic modeling, water quality assessment, treatment technologies, and detailed cost analysis would be necessary to evaluate the practical implementation of such systems. Despite these limitations, the study demonstrates that spatial data analysis can provide valuable insights into how existing community infrastructure may contribute to alternative water resource strategies in regions experiencing seasonal water scarcity.

4. Conclusion

This study explored the spatial configuration of mosque-based wudu water collection networks in Lombok Barat using a combination of K-Means clustering and Minimum Spanning Tree (MST) analysis. Based on spatial data from 940 mosque locations, the clustering framework identified 25 local clusters and five larger aggregation zones, representing potential spatial groupings for decentralized water collection. The MST network analysis produced a minimum total connection length of 411,757.28 meters, providing a distance-based estimate of the most efficient connectivity structure among mosque nodes. The results demonstrate that spatial clustering and graph-based optimization can be used to analyze the geographic distribution of mosque infrastructure and estimate efficient network configurations for potential resource collection systems. The estimated daily volume of approximately 282,000 liters of wudu water indicates that mosque-generated greywater may represent a locally available supplementary water resource. However, this estimate is based on simplified assumptions and should be interpreted as an indicative approximation rather than a verified operational supply. It is important to note that the proposed network represents a preliminary spatial planning model derived from geographic coordinates and distance-based optimization. The analysis does not incorporate hydraulic simulation, infrastructure design constraints, land availability, treatment system performance, or detailed economic feasibility assessments. Therefore, the results should not be interpreted as a finalized engineering design or immediate implementation plan. Future research could extend this work by incorporating water quality assessment, treatment system design, hydraulic modeling, and irrigation demand analysis. Integrating these aspects would provide a more comprehensive evaluation of the feasibility of mosque-based greywater reuse systems in water-scarce regions.

Author Contributions. **Sutanto**: Conceptualization, methodology, data curation, and writing original draft preparation. **Retno Tri Vulandari**: Formal analysis, validation, methodology development, and simulation modeling. **Tyas Titah Nareswari**: Investigation, data analysis, visualization, and writing—review and editing. All authors have read and agreed to the published version.

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