Efficient Integration of Water Demand using Fuzzy Analytical Hierarchical Process Model with Geographic Information System in Vientiane Capital, Lao PDR

Singharaj, M.,[1] **Jeefoo, P.,**[1,2*] **Chaikaew, N.**[1,2] **Iamchuen, N.,**[1,2] **Paengwangthong, W.**[1,2] **and Sukpromsun, B.**[1,2]
[1]Applied Geoinformatics, School of Information and Communication Technology, University of Phayao, Thailand, E-mail: 66025166@up.ac.th
[2]Geographic Information Science, School of Information and Communication Technology, University of Phayao, Thailand, E-mail: phaisarn.je@up.ac.th,* nakarin.ch@up.ac.th, niti.ia@up.ac.th, wipop.pa@up.ac.th, boonsiri.su@up.ac.th
*Corresponding Author

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Abstract

Water demand management remains a critical challenge in rapidly urbanizing cities, particularly in Southeast Asia where infrastructure expansion often lags behind demographic growth. This study develops an integrated framework that combines the Fuzzy Analytic Hierarchy Process (FAHP) with Geographic Information System (GIS) to analyze domestic water demand in Vientiane Capital, Lao PDR. Five criteria consist of population density, household size, access to piped water, distance from water sources, and elevation were evaluated through expert-based pairwise comparisons using FAHP, which effectively addresses uncertainty and subjectivity in decision-making. The derived weights were incorporated into spatial datasets and analyzed using the Weighted Overlay technique in ArcGIS Pro to generate a Water Demand Suitability Map. Quantitative results classified water demand into five levels: very high (4.40%), high (60.11%), medium (7.34%), low (8.79%), and very low (19.36%). High and very high demand zones were concentrated in the urban core districts Chanthabouly, Xaisettha, Sikhotabong, Sisattanak, and Hatxayfong. These areas host most water treatment plants, piped distribution systems, and economic activities. In contrast, medium- to very low-demand areas were found in peripheral districts such as Sangthong, Naxaythong, Xaithani, and Pakngum, where approximately 20% of villages lack piped water access and seasonal droughts exacerbate water scarcity. Access to piped water (weight = 0.503) and population density (weight = 0.231) emerged as the most influential determinants, underscoring the importance of infrastructure and demographic pressures in shaping demand. The novelty of this study lies in extending FAHP-GIS applications from hazard and drought assessments to domestic water demand analysis, thereby providing a replicable tool for prioritizing infrastructure investment and resource allocation. Limitations include reliance on expert judgment for weighting and the exclusion of climate change projections, which should be addressed in future research. Overall, the integrated FAHP-GIS approach offers a practical and innovative decision-support framework for policymakers and water authorities to design resilient strategies for sustainable water resource management under conditions of rapid urbanization and climate variability.

Keywords: Fuzzy Analytic Hierarchy Process (FAHP), Geographic Information System (GIS), Urbanization and Infrastructure, Vientiane Capital – Lao PDR, Water Demand Management

1. Introduction

Water is a vital natural resource essential for sustaining human life and driving economic activities across all regions of the world. Its role extends beyond domestic consumption to agriculture, industry, and the preservation of ecological balance. However, continuous population growth and rapid economic development have significantly increased water demand in all sectors. Inefficient water resource management in many countries including administration, planning, and system maintenance combined with the intensifying impacts of climate change, has disrupted the hydrological cycle and reduced the availability of water in natural sources. These challenges have led to shortages of clean water for domestic and industrial use, particularly in rapidly urbanizing area [1].

The Lao People's Democratic Republic (Lao PDR), despite being endowed with abundant water resources and several major rivers, continues to face challenges in managing clean water supply for domestic consumption, especially in fast-growing urban centers. According to the Asian Development Bank (2020), only 78 percent of the urban population in Lao PDR has access to safe and clean piped water [2]. Vientiane Capital, as the national capital and economic hub, has experienced rapid economic growth and infrastructure development, with a dense population of 948,477 inhabitants in 2020 [3]. Large-scale development projects, such as the Lao–China high-speed railway, special economic zones, and new urban development initiatives, have further intensified the demand for clean water. A study by the World Bank (2021) reported that water demand in Vientiane Capital has been increasing at an average rate of 8–10 percent per year, while the capacity of water supply systems has expanded by only 5 percent annually [4].

Managing urban water supply in such rapidly expanding areas requires effective tools and methodologies for analyzing and forecasting water demand. Geographic Information Systems (GIS), combined with Multi-Criteria Decision Analysis (MCDA), provide a robust framework for this purpose [5] and [6]. In particular, the Analytic Hierarchy Process (AHP) and the Fuzzy Analytic Hierarchy Process (FAHP) offer significant advantages for integrating water demand across multiple sectors, including agriculture, industry, and domestic consumption [7]. The strength of AHP lies in its clear hierarchical structure, which simplifies complex problems, supports pairwise comparisons to systematically evaluate the importance of factors, and incorporates consistency checks to ensure reliability of decisions [8]. FAHP, on the other hand, addresses uncertainty by applying fuzzy sets to accommodate imprecise or ambiguous expert judgments [9]. It is particularly suitable for subjective data, such as expert or community opinions, and enhances decision-making accuracy by reducing bias and uncertainty. Moreover, FAHP enables the integration of diverse data sources, including surveys, interviews, and workshops [10] and [11].

Previous research has typically examined drought risk or water stress, with limited attention to socio-economic and infrastructural dimensions of domestic water demand. This study addresses that gap by integrating FAHP with GIS to incorporate demographic and infrastructural criteria [12] and [13]. In Southeast Asia, urban water demand management has been approached through methods ranging from statistical forecasting to spatial analysis. For example, FAHP-GIS was applied to assess drought risk in Thailand, showing that FAHP reduces uncertainty in expert-based decisions but requires highly detailed spatial data [14]. Similarly, GIS was use to analyze water stress in major Southeast Asian cities, finding that densely populated areas are particularly vulnerable to scarcity [15]. While these studies demonstrate the utility of FAHP and GIS in water resource planning, they often overlook socio-economic and infrastructural integration [16]. To address this limitation, the present study develops a FAHP-GIS framework that incorporates demographic, infrastructural, and spatial criteria to evaluate domestic water demand in Vientiane Capital. This framework offers policymakers a more comprehensive tool for prioritizing investments and designing resilient water management strategies.

This study addresses that gap by applying FAHP–GIS specifically to domestic water demand in Vientiane Capital. The novelty lies in integrating demographic, infrastructural, and spatial criteria population density, household size, access to piped water, distance from water sources, and elevation into a unified framework. By doing so, the research advances existing knowledge by extending FAHP–GIS applications beyond hazard assessment to demand analysis, providing a replicable tool for policymakers to identify priority zones for infrastructure investment. Furthermore, the study contributes to sustainable urban water management by highlighting the most influential determinants of demand and offering insights into demand supply imbalances under conditions of rapid urbanization and climate variability.

2. Materials and Methods

2.1 Study Area

This study focuses on analyzing the service areas of the water supply system in Vientiane Capital, Lao People's Democratic Republic (Figure 1), covering the service zones of seven water treatment plants (WTPs), namely Chinaimo WTP, Kaolieo WTP, Dongmarkhay WTP I, Dongmarkhay WTP II, Dongbang WTP, Thadeua WTP, and Saendin WTP. The study area is situated within the Mekong River basin, with the Mekong River flowing along the southern and western boundaries, and the Ngum River flowing along the eastern boundary.

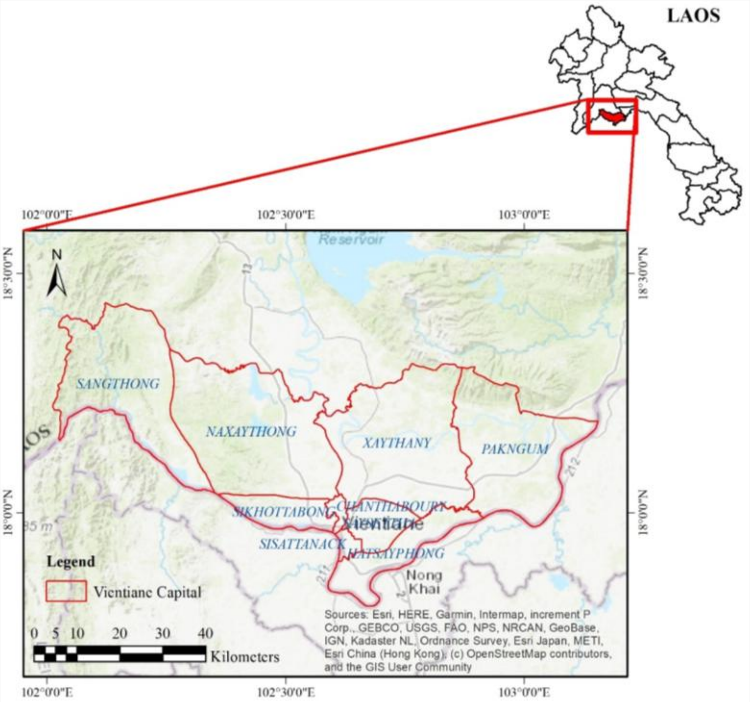


Figure 1: Vientiane Capital, Lao People's Democratic Republic

Table 1: Fuzzy scale for pairwise comparison

Definition	Crisp scale	Fuzzy scale
Equal importance	1	(1, 1, 1)
Somewhat more important	3	(2, 3, 4)
Much more important	5	(4, 5 ,6)
Very much more important	7	(6, 7, 8)
Absolutely more important	9	(8, 9, 9)
Intermediate values	2, 4, 6, 8	(x-1, x, x+1)

It encompasses several administrative districts, including Chanthabouli, Sikhottabong, Saysettha, Naxaithong, Sisattanak, and Pakngum. The total production capacity of the water supply system in the study area amounts to 348,000 cubic meters per day, with service areas distributed according to the capacity of each plant. This reflects the development of water supply infrastructure to accommodate urban expansion during 2019 and the planned development up to 2030. Most service areas are concentrated in urbanized zones, particularly in the central part of Vientiane Capital, where population density and economic activities are high, primarily served by Chinaimo and Kaolieo WTPs. Meanwhile, the peripheral areas, which are experiencing continuous urban expansion, are supplied by other WTPs in line with the city's long-term development plan.

2.2 Fuzzy Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) is a decision support system designed to address complex problems by structuring them into a hierarchical framework [17]. It enables the prioritization of criteria through measurement scores derived from expert judgments; however, the accuracy of results can be affected by ambiguity in score assignment. To overcome this limitation, AHP was extended with fuzzy logic theory, resulting in the Fuzzy Analytic Hierarchy Process (FAHP) [17] and [18]. FAHP operates similarly to AHP but offers enhanced capability in handling uncertainty and subjectivity in decision-making [19]. In this approach, each element is assigned a membership grade on a fuzzy scale, with the triangular fuzzy number (TFN) serving as a simple yet effective function [20]. TFN is particularly useful in ambiguous environments, where it helps resolve decision-making challenges [21]. Unlike conventional AHP, which relies on single numerical values for pairwise comparisons, FAHP employs fuzzy scales, as illustrated in Table 1 [22] and [23]. The methodological steps of FAHP are outlined in detail by [24] and [25].

Step 1. Hierarchical structure development: The primary and secondary criteria are established in accordance with the overarching objectives.

Step 2. Calculation of the fuzzified pairwise comparison matrix: Equation 1 contains the pairwise comparison, where M_{gij} ($i = 1, 2, ..., n$ and $j = 1, 2, ..., m$) are TFNs [25].

$$\left(M_{gi}^{j}\right)_{nxm} = \begin{bmatrix} M_{g1}^{1} & M_{g1}^{2} & \cdots & M_{g1}^{m} \\ M_{g2}^{1} & M_{g2}^{2} & \cdots & M_{g2}^{m} \\ \vdots & \vdots & & \vdots \\ M_{gn}^{1} & M_{gn}^{2} & \cdots & M_{gn}^{m} \end{bmatrix} = \begin{bmatrix} (1,1,1) & \left(l_{1_2}, m_{1_2}, u_{1_2}\right) & \cdots & \left(l_{1_m}, m_{1_m}, u_{1_m}\right) \\ \left(l_{2_1}, m_{2_1}, u_{2_1}\right) & (1,1,1) & \cdots & \left(l_{2_m}, m_{2_m}, u_{2_m}\right) \\ \vdots & \vdots & \vdots & \vdots \\ \left(\frac{1}{u_{n_1}}, \frac{1}{m_{n_1}}, \frac{1}{l_{n_1}}\right) & \left(\frac{1}{u_{n_2}}, \frac{1}{m_{n_2}}, \frac{1}{l_{n_2}}\right) & \cdots & (1,1,1) \end{bmatrix}$$

Equation 1

Specifically, *l* represents the lower bound, *m* the most likely value, and *u* the upper bound in the final matrix.

Step 3: Calculation of the imprecise synthetic extent: This phase is computed using Equation 2.

$$S_i = \sum\nolimits_{j=1}^{m} M_{gi}^{j} \times \left[\sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{m} M_{gi}^{j}\right]$$

Equation 2

Where S_i is the synthetic extent value of the pairwise comparison and $\sum\nolimits_{j=1}^{m} M_{gi}^{j}$ is the total number of TFNs. Additional information is provided in Equation 3 to Equation 5, correspondingly.

$$\sum\nolimits_{j=1}^{m} M_{gi}^{j} = \left[\sum\nolimits_{j=1}^{m} l_j, \sum\nolimits_{j=1}^{m} m_j, \sum\nolimits_{j=1}^{m} u_j\right]$$

Equation 3

$$\sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{m} M_{gi}^{j} = \left(\sum\nolimits_{i=1}^{n} l_i, \sum\nolimits_{i=1}^{n} m_i \sum\nolimits_{i=1}^{n} u_i\right)$$

Equation 4

$$\left[\sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{m} M_{g}^{j}\right]^{-1} = \left(\frac{1}{\sum\nolimits_{i=1}^{n} l_i}, \frac{1}{\sum\nolimits_{i=1}^{n} m_i}, \frac{1}{\sum\nolimits_{i=1}^{n} u_i}\right)$$

Equation 5

Step 4. Utilize Equation 6 to determine the degree of probability.

$$V\left(S_i \geq S_j\right) = \begin{cases} 1 & m_i \geq m_j \\ 0 & if \quad l_j \geq u_i \\ \dfrac{l_j - u_i}{\left(m_i - u_i\right) - \left(m_j - l_j\right)} & otherwise \end{cases}$$

Equation 6

In the case of S_i is greater than S_j, then $V\left(S_i \geq S_j \middle| j = 1, 2, ..., m; \neq j\right) =$ $\min V\left(S_i \geq S_j \mid j = 1, 2, ..., m; \neq j\right)$.

Step 5. Determine the weight vector: The definition of a weight vector is defined in Equations 7 and 8:

$$W_i^{'} = \min V\left(S_i \geq S_j \middle| j = 1, 2, ..., i \neq j\right)$$

Equation 7

$$W_i = \frac{w_i^{'}}{\sum\nolimits_{i=1}^{n} w_i^{'}}$$

Equation 8

Where the term *W*, is defined as $(w_1, w_2, ..., w_n)^T$, is a weight vector that has been normalized. The non-fuzzy number (w_i) for each weight will be derived then.

Step 6. Consistency determination: The comparison matrix is established by the consistency of the evaluation, as indicated by the expert decision. Equation 9 is applied to calculate the consistency index (*CI*), which is used to determine the degree of consistency.

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

Equation 9

Where $\lambda_{\max}$ and n are the maximum eigenvector derived from the calculation of pairwise comparison matrix and the number of factors. The consistency ratio (*CR*) is computed using Equation 10 to certify the acceptance of the degree of consistency.

$$CR = \frac{CI}{RI}$$

Equation 10

RI is the random inconsistency which depends on the number of factors. The consistency of the judgment matrix is satisfactory, as indicated by $CR < 0.1$. The consistency of the judgment matrix must be reevaluated when *CR* is greater than or equal to 0.1 [22].

2.3 Methods

Referring to Figure 2, the flowchart presents the methodological framework for deriving domestic water demand maps through the integration of FAHP and GIS. FAHP was employed to calculate the weights of both main and sub-criteria related to water demand, including population density, household size, access to piped water, distance from water sources, and elevation, with detailed descriptions provided in Section 2.3.5.

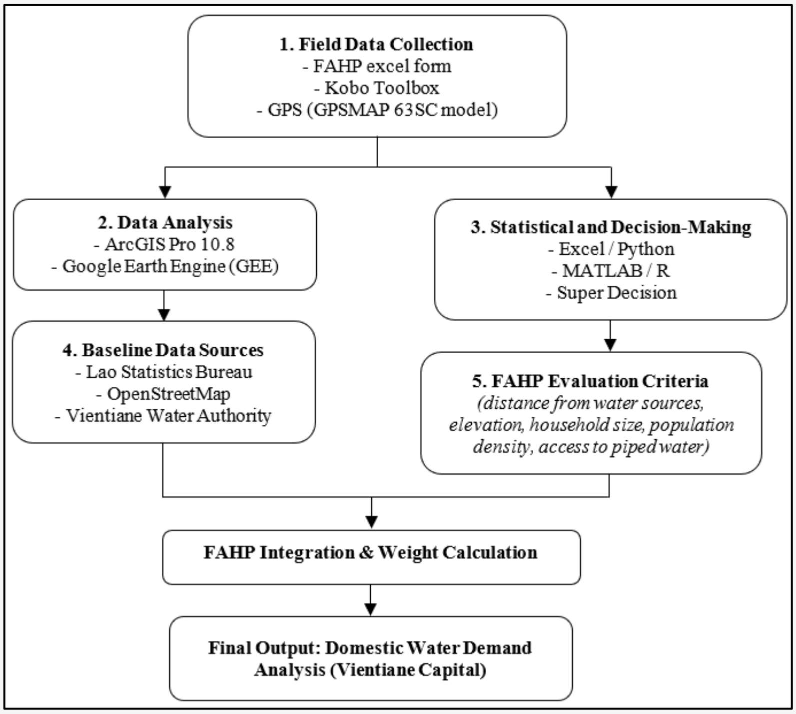


Figure 2: Domestic water demand analysis methodology

These weighted criteria were incorporated into spatial datasets and analyzed using the Weighted Overlay technique in ArcGIS Pro to produce water demand suitability maps. This approach enables a systematic evaluation of demand levels across urban and peri-urban areas, highlighting zones of vulnerability where infrastructure limitations and demographic pressures converge. In this context, vulnerability refers to the conditions and capacities that affect the reliability of water supply systems and the resilience of communities to demand–supply imbalances [26].

To further quantify the spatial distribution of domestic water demand risk, a Water Demand Risk Score (WDRS) was developed. The WDRS was calculated as the product of the Water Demand Hazard Score (WDHS) and the Water Demand Vulnerability Score (WDVS). In this framework, WDHS represents the intensity of demand pressure, derived from factors such as population density, household size, and access to piped water, while WDVS reflects the susceptibility of communities and infrastructure to demand supply imbalances, incorporating conditions such as limited service coverage and elevation constraints. Multiplying these two dimensions provides a composite measure that captures both the magnitude of demand stress and the system's vulnerability. This formulation is consistent with established risk assessment approaches, where risk is commonly expressed as the interaction between hazard and vulnerability [26]. By applying this method, the study ensures that areas with both high demand pressure and weak infrastructure are prioritized in water resource planning and management (Equation 11).

$$WDRS = WDHS \times WDVS$$

Equation 11

The water demand score is calculated using Equation 12:

$$\begin{aligned} WDHS = {} & WM_{Pd} \cdot WSub_{Pd} + WM_{HS} \cdot WSub_{HS} \\ & WM_{Apw} \cdot WSub_{Apw} + WM_{Dws} \cdot WSub_{Dws} \\ & WM_{E} \cdot WSub_{E} \end{aligned}$$

Equation 12

Where WM_{pd}, WM_{Hs}, WM_{Apw}, WM_{Dws}, and WM_{E} are the weights of main-criteria for water demand, including population density, household size, access to piped water, distance from water sources, and elevation respectively. $WSub_{Pd}$, $WSub_{Hs}$, $WSub_{Apw}$, $WSub_{Dws}$, and $WSub_{E}$ indicate the weights of each. The score of vulnerability is computed from Equation 13.

$$WDVS = WM_{Pd} \times WSub_{Pd}$$

Equation 13

Where WM_{Pd} and $WSub_{Pd}$ represent the weights of the main and sub-criteria associated with population density. The derived weight values were incorporated into the GIS database to construct vulnerability layers. Using Equation 12 and Equation 13, the Water Demand Hazard Score (WDHS) and Water Demand Vulnerability Score (WDVS) were computed and subsequently reclassified. The vector-based risk factors were converted into raster format with a spatial resolution of 30 × 30 m to ensure consistency in spatial analysis. Finally, the weighted overlay of raster layers, as defined in Equation 11, was employed to calculate the Water Demand Risk Score (WDRS). The resulting risk maps were classified into low, medium, and high levels using the standard deviation method, thereby enabling spatial identification of areas with varying degrees of domestic water demand risk (adapted from [22]). To analyze domestic water demand using the Fuzzy Analytic Hierarchy Process (FAHP) model in Vientiane Capital, a combination of field survey tools, spatial analysis software, statistical decision-making tools, and baseline datasets were employed. The methodological framework is outlined as follows (Figure 2).

2.3.1 Field data collection tools

a) FAHP Excel form: Designed to allow experts to perform pairwise comparisons of key factors, including population density, distance from water sources, slope, household size, and access to piped water services. The pairwise comparison scores were obtained through consultations with seven experts, including three academics specializing in water resource management, two government officials from the Department of Water Supply, and two GIS practitioners. Each expert independently provided judgments on the relative importance of criteria. To ensure consistency and reliability, the scores were aggregated using the geometric mean method, as recommended in the FAHP framework. This approach minimized individual bias and produced a balanced set of weights for constructing the decision matrix.

b) KoboToolbox: Utilized for collecting responses from experts and local residents.

c) GPS: Applied to record the geographic locations of water sources and consumption areas.

2.3.2 Spatial analysis tools

(a) ArcGIS Pro: Used to analyze spatial datasets such as population density, land use, and distance from water sources. Weighted Overlay tools were applied to integrate multiple criteria, while Model Builder was employed to automate analytical workflows.

(b) Google Earth Engine (GEE): Implemented for satellite image analysis, including land use change detection. Normalized Difference Vegetation Index (NDVI) and Land Use/Land Cover (LULC) the year of 2025 data were used to identify areas with high water demand.

2.3.3 Statistical and decision-making tools

(a) Microsoft Excel and Python (Pandas, NumPy): Applied to calculate Triangular Fuzzy Numbers (TFN) and Consistency Ratios in FAHP, as well as to conduct statistical analysis of questionnaire data.

(b) MATLAB: Used for advanced FAHP analysis, including aggregation of multiple expert opinions.

(c) Super Decisions Software: A specialized tool for AHP/FAHP analysis, enabling hierarchical structuring and automated weight calculation.

2.3.4 Baseline data sources

(a) Lao Statistics Bureau: Provided demographic, income, and land use data.

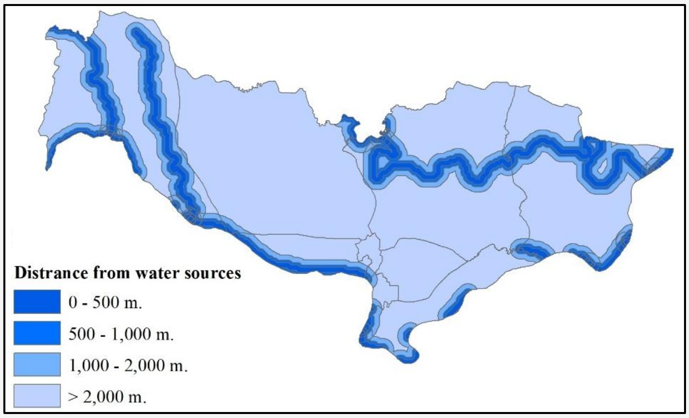


Figure 3: Distance from water sources

(b) OpenStreetMap / Lao National Geoportal: Supplied fundamental geospatial datasets.

(c) Vientiane Capital Water Supply Authority: Provided actual water consumption records.

2.3.5 FAHP Evaluation Criteria

The FAHP analysis incorporated three dimensions of criteria:

Distance from Water Sources: Data on rivers, streams, ponds, canals, and wetlands were obtained with the support of the Department of Irrigation, Lao PDR, in 2025. The distance from water sources was categorized into four levels: less than 500 meters, 500-1,000 meters, 1,000-2,000 meters, and more than 2,000 meters, respectively. To ensure consistency in the integration of spatial datasets, the distance from water sources was calculated using the Euclidean Distance function in GIS, based on the main stream lines. This process generated a raster layer representing the distance from each location to the streams. The raster was subsequently resampled and reclassified to match the resolution and scale of other spatial layers, including administrative boundaries, household size, population density, and access to piped water. This procedure allowed effective overlay and integration with the other datasets (Figure 3).

Elevation: Spatial elevation data were collected from the National Mapping Agency of Lao PDR, as well as relevant organizations both within and outside the study area. The elevation was found to range between 115 and 680 meters (Figure 4).

Household Size: Household size and population density data (Figures 5 – 6) were obtained from the Lao Statistics Bureau in 2025. The analysis revealed a significant relationship with domestic water consumption. Larger households (more than four members) were found to use, on average, 20–30% less water per person compared to smaller households (one to two members). This difference is attributed to shared water use in activities such as washing, cleaning, and gardening.

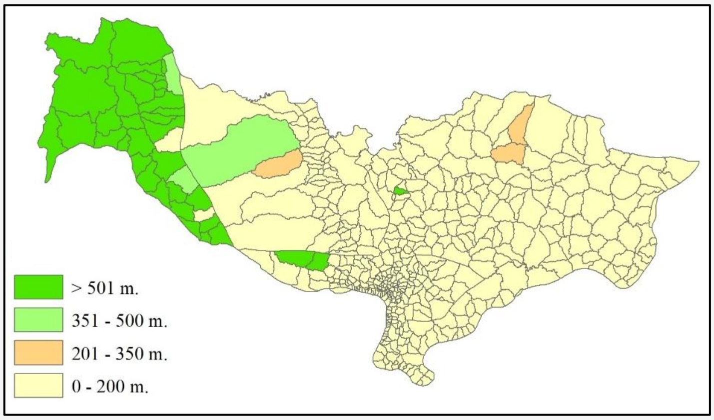


Figure 4: Elevation

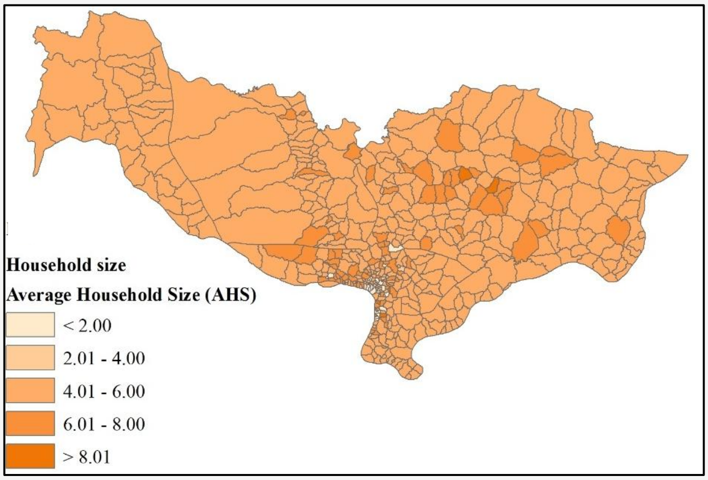


Figure 5: Household size in the year of 2025

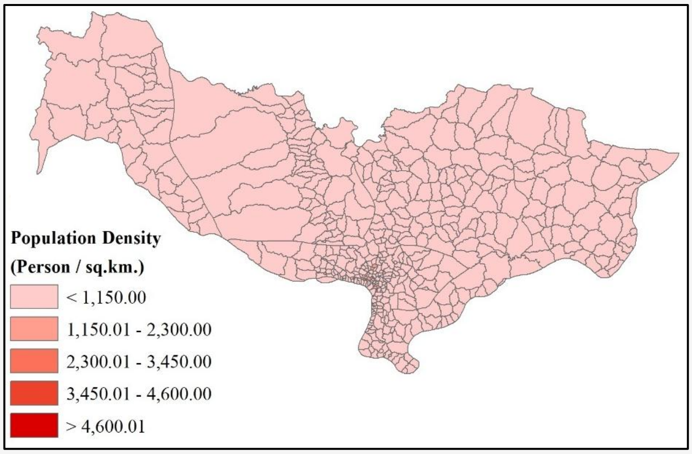


Figure 6: Population density

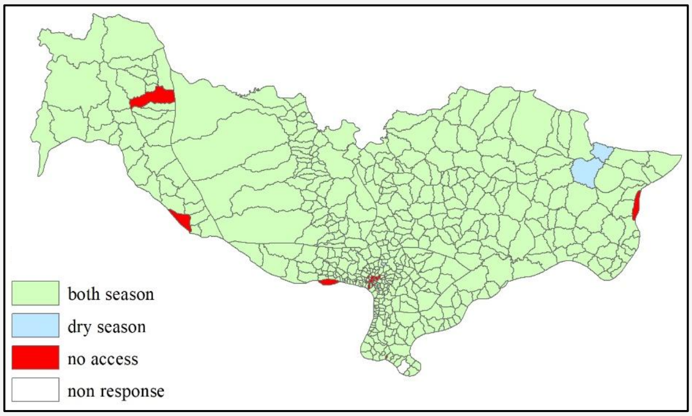


Figure 7: Access to piped water

Population Density: Population density data were derived from the Lao Statistics Bureau (2020) and processed using GIS techniques to calculate the number of inhabitants per square kilometer. The results indicate that the central districts of Vientiane Capital, such as Chanthabouly and Sikhottabong, exhibit the highest population density, exceeding 3,000 persons per km^2. These areas correspond to zones of elevated water demand, reflecting the direct relationship between demographic concentration and resource consumption. In contrast, peripheral districts show relatively lower density, which aligns with reduced water demand pressure.

Access to Piped Water: Data on the water supply system and pipelines were obtained with the support of the Vientiane Capital Water Supply Company in 2025. The distance from water sources was classified into three categories: both season, dry season, and no access (Figure 7).

The evaluation criteria were selected to capture both demographic and infrastructural determinants of water demand:

Access to piped water: The most influential factor, distinguishing between areas with year-round service, seasonal service, and no access.

Population Density: High-density urban zones exhibit elevated demand due to concentrated households and economic activities.

Household Size: Medium-sized households (4-6 members) showed the highest relative demand, reflecting shared water use across multiple activities.

Elevation: Lower elevation areas (<200 m) correspond to urban centers with easier infrastructure access, while higher elevations are less developed.

Distance from Water Sources: Proximity to rivers and canals (<500 m) facilitates water availability and correlates with higher demand.

Integration of FAHP with GIS was undertaken to develop a spatial model. After obtaining the weights of each factor through the FAHP process, these weights were incorporated into spatial datasets generated in ArcGIS for analysis using the Weighted Overlay technique. This procedure involved standardizing the measurement scales of all factors to a common range (e.g., suitability levels from 1 to 5), multiplying each spatial layer by its corresponding FAHP-derived weight, and aggregating the results across all layers to produce a Water Demand Suitability Map. The outcome of this process enabled the classification of areas within Vientiane Capital into five levels of water demand: very high, high, moderate, low, and very low. These results provide a strategic basis for planning the expansion of urban water supply services.

3. Results and Discussion

3.1 Weight Analysis

According to the FAHP in section 2.2 and the hierarchical structure shown in Figure 8, pairwise comparisons of elements in cluster are conducted with respect to relative important. The hazard factors include slope, floodwater depth, and soil drainage. Land use is defined as vulnerability. To produce pairwise comparison matrices, six experts from different Thai firms were invited to complete the designed questionnaires. Before assigning the scores, the authors explained in details of description and crisp scale (Table 1) in the questionnaires and ranking function. By computing average values of the experts' answers, the average values were rounded to their closest crisp scale to develop the fuzzy judgment matrices using fuzzy scale as shown in Table 2 for main-criteria and Tables 3 to 6 for sub-criteria. The processes and equations of FAHP were developed in the excel space sheet to calculate essential variables such as λ_{max}, CI, RI, and CR depicted in Tables 2 to 6. The λ_{max} values are closed to the number of factors and CR < 0.1 for all matrices which satisfied the condition. Finally, the weight values of the main- and sub-criteria were computed in which revealed in the parentheses of Figure 8.

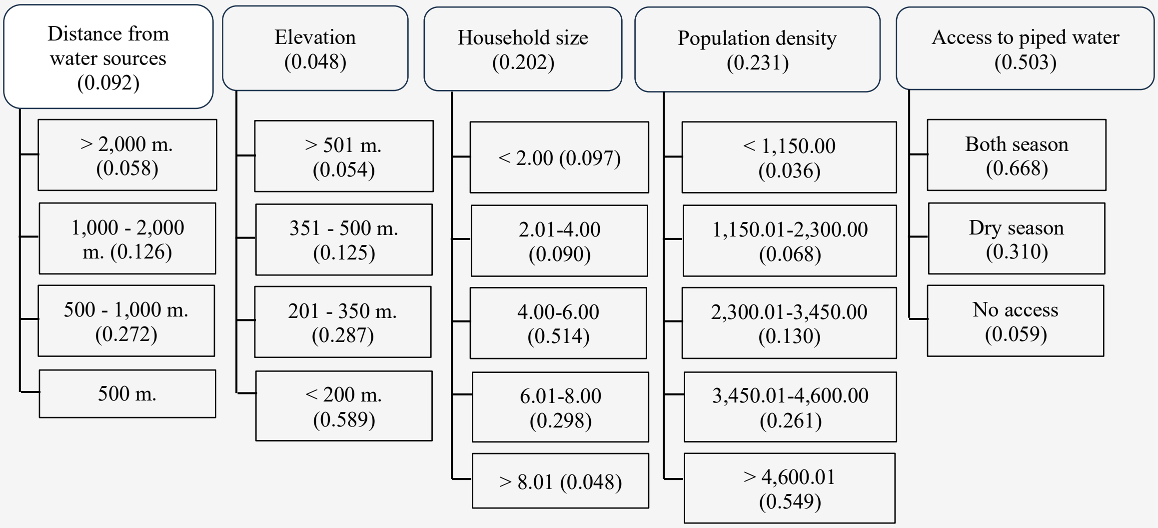


Figure 8: Hierarchical structure of efficient integration of water demand in Vientiane Capital

Table 1: Main-criteria judgment matrix'

Main-criteria	Access to piped water	Population density	Household size	Distance from water sources	Elevation
Access to piped water	1,1,1	2,3,4	3,4,5	4,5,6	6,7,8
Population density	1/4,1/3,1/2	1,1,1	1,2,3	2,3,4	3,4,5
Household size	1/5,1/4,1/3	1/3,1/2,1/1	1,1,1	4,5,6	3,4,5
Distance from water sources	1/6,1/5,1/4	1/4,1/3,1/2	1/6,1/5,1/4	1,1,1	2,3,4
Elevation	1/8,1/7,1/6	1/5,1/4,1/3	1/5,1/4,1/3	1/4,1/3,1/2	1,1,1
$\lambda_{max} = 5.41, CI = 0.102, RI = 1.11, CR = 0.092$					

Table 2: Sub-criteria judgment matrix of access to piped water

Sub-criteria of access of piped water	Both season	Dry season	No access
Both season	1,1,1	2,3,4	8,9,9
Dry season	1/4,1/3,1/2	1,1,1	6,7,8
No access	1/9,1/9,1/8	1/8,1/7,1/6	1,1,1
$\lambda_{max} = 3.11$, $CI = 0.056$, $RI = 0.52$, $CR = 0.10$			

Table 3: Sub-criteria judgment matrix of population density

Main-criteria	< 1,150.00	1,150.01 – 2,300.00	2,300.01 – 3,450.00	3,450.01 – 4,600.00	> 4,600.01
< 1,150.00	1,1,1	1/4,1/3,1/2	1/6,1/5,1/4	1/8,1/7,1/6	1/9,1/9,1/8
1,150.01 – 2,300.00	2,3,4	1,1,1	1/4,1/3,1/2	1/6,1/5,1/4	1/9,1/9,1/8
2,300.01 – 3,450.00	4,5,6	2,3,4	1,1,1	1/4,1/3,1/2	1/8,1/7,1/6
3,450.01 – 4,600.00	6,7,8	4,5,6	2,3,4	1,1,1	1/4,1/3,1/2
> 4,600.01	8,9,9	7,8,9	6,7,8	2,3,4	1,1,1

λ_{max} = 5.37, CI = 0.089, RI = 1.11, CR = 0.080

Table 4: Sub-criteria judgment matrix of household size

Main-criteria	< 2.00	2.01 – 4.00	4.01 – 6.00	6.01 – 8.00	> 8.01
< 2.00	1,1,1	1,1,1	1/6,1/5,1/4	1/6,1/5,1/4	2,3,4
2.01 – 4.00	1,1,1	1,1,1	1/8,1/7,1/6	1/6,1/5,1/4	2,3,4
4.01 – 6.00	4,5,6	6,7,8	1,1,1	2,3,4	6,7,8
6.01 – 8.00	4,5,6	4,5,6	1/4,1/3,1/2	1,1,1	4,5,6
> 8.01	1/4,1/3,1/2	1/4,1/3,1/2	1/8,1/7,1/6	1/6,1/5,1/4	1,1,1

λ_{max} = 5.34, CI = 0.084, RI = 1.11, CR = 0.076

Table 5: Sub-criteria judgment matrix of distance from water sources

Main-criteria	0 – 500 m	500 – 1,000 m.	1,000 – 2,000 m.	> 2,000 m
0 – 500 m.	1,1,1	2,3,4	4,5,6	6,7,8
500 – 1,000 m.	1/4,1/3,1/2	1,1,1	2,3,4	4,5,6
1,000 – 2,000 m.	1/6,1/5,1/4	1/4,1/3,1/2	1,1,1	2,3,4
> 2,000 m.	1/8,1/7,1/6	1/6,1/5,1/4	1/4,1/3,1/2	1,1,1

λ_{max} = 4.18, CI = 0.060, RI = 0.89, CR = 0.068

Table 6: Sub-criteria judgment matrix of elevation

Main-criteria	0 – 200 m	200 – 350 m.	351 – 500 m.	> 501 m
0 – 200 m.	1,1,1	2,3,4	4,5,6	7,8,9
200 – 350 m.	1/4,1/3,1/2	1,1,1	2,3,4	5,6,7
351 – 500 m.	1/6,1/5,1/4	1/4,1/3,1/2	1,1,1	2,3,4
> 501 m.	1/9,1/8,1/7	1/7,1/6,1/5	1/4,1/3,1/2	1,1,1

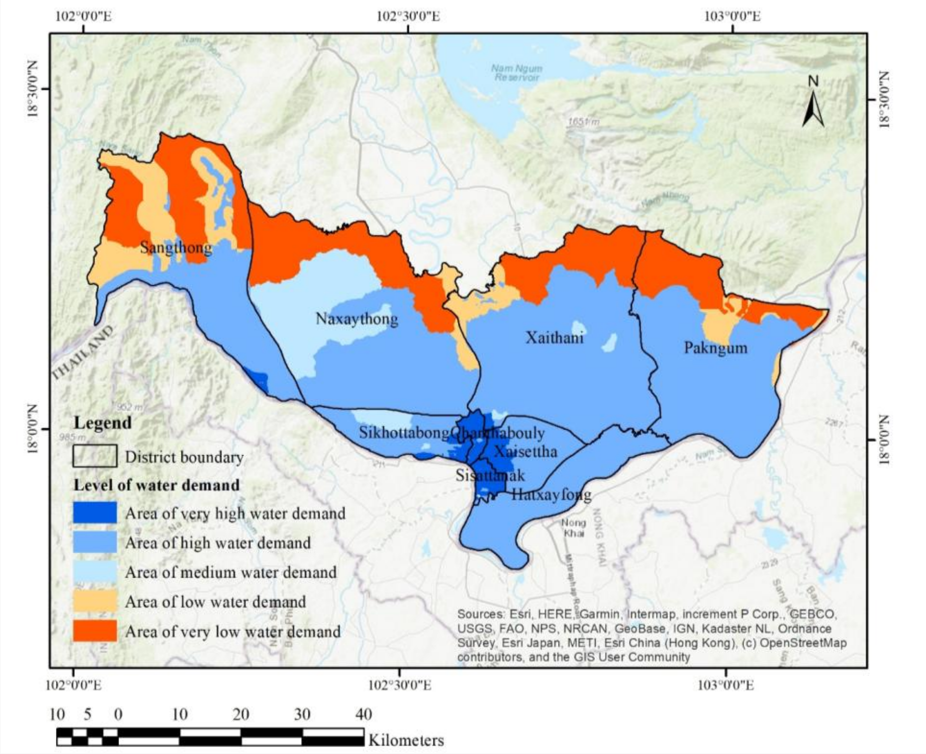
λ_{max} = 4.16, CI = 0.053, RI = 0.89, CR = 0.060

The application of the Fuzzy Analytic Hierarchy Process (FAHP) combined with GIS enabled the systematic evaluation of domestic water demand in Vientiane Capital. The weight analysis revealed that access to piped water (0.50) was the most influential factor, followed by population density (0.23) and household size (0.20). In contrast, distance from water sources (0.09) and elevation (0.05) contributed less significantly to the overall demand. These findings emphasize that the availability of piped water infrastructure and demographic characteristics are the primary drivers of water consumption in rapidly urbanizing areas.

The sub-criteria analysis further highlighted the importance of service reliability. Areas with piped water available in both seasons received the highest weight (0.67), while regions with no access to piped water were assigned the lowest (0.06). Similarly, high population density (>4,600 persons/km²) was strongly associated with elevated water demand (0.5492), reflecting the concentration of households and economic activities in central districts. Household size also played a notable role, with medium-sized households (4–6 members) showing the highest relative weight (0.51), indicating that shared water use within households contributes to higher overall consumption.

The spatial integration of FAHP-derived weights into GIS allowed for a nuanced classification of domestic water demand across Vientiane Capital. The Water Demand Suitability Map revealed five distinct demand levels, ranging from very high to very low. Approximately 64.5% of the total area (very high and high demand combined) is concentrated in the urban core, underscoring the strong influence of population density, infrastructure availability, and economic activity on water consumption patterns. These zones correspond to districts such as Chanthabouly, Xaisettha, Sikhotabong, Sisattanak, and Hatxayfong, which host major water treatment facilities and benefit from extensive piped water distribution networks. These findings are consistent with [15], who reported that high-density urban areas in Southeast Asia face elevated water stress. However, unlike their study, our results highlight the critical role of piped water infrastructure as the most influential determinant. Their role as centers of trade, investment, and urban expansion further reinforces the concentration of demand (Figure 9).

In contrast, peripheral districts including Sangthong, Naxaythong, Xaithani, and Pakngum exhibit medium to very low demand (Table 7), accounting for nearly 36% of the study area. Field surveys confirmed that water supply in these districts is unevenly distributed, with approximately one-fifth of villages lacking access to piped water entirely. Residents in these areas rely heavily on groundwater extraction, which is vulnerable to depletion and contamination. Seasonal droughts, particularly between April and June, exacerbate water scarcity and highlight the fragility of water security in rural and transitional zones. The coexistence of high-demand urban centers and underserved rural communities illustrates the dual challenge of managing rapid urbanization while addressing persistent infrastructure gaps. The district-level analysis (Table 8) provides further insight into spatial disparities. For instance, Xaithani and Naxaythong cover extensive areas with mixed demand levels, reflecting ongoing urban expansion alongside rural settlements. Sangthong and Pakngum, despite their large geographic size, remain dominated by low and very low demand zones due to limited infrastructure and lower population density.



Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community

Figure 9: Spatial distribution of domestic water demand levels in Vientiane Capital derived from the FAHP–GIS model, classified into five categories (very high to very low)

Table 7: Area of water demand and percentage

Water demand	Area (sq.km.)	Percentage (%)
Area of very high-water demand	175.73	4.40
Area of high-water demand	2,401.67	60.11
Area of medium-water demand	293.13	7.34
Area of low-water demand	351.29	8.79
Area of very low-water demand	773.42	19.36
Total area	**3,995.23**	**100.00**

Table 8: Area of water demand by district

District	Area of water demand (sq.km.)					Total
	Very high	High	Medium	Low	Very low	
1. Chanthaboury	24.560	0.767	0.047	0.015	0.000	25.388
2. Hatsayphong	0.000	240.331	0.000	0.000	0.000	240.331
3. Naxaythong	0.000	384.811	252.341	28.403	237.923	903.478
4. Pakngum	0.000	567.607	0.000	43.202	164.959	775.760
5. Sangthong	79.019	373.649	0.000	187.334	219.039	859.042
6. Sikhottabong	17.339	102.425	28.465	0.038	0.000	148.266
7. Sisattanack	24.066	2.231	0.264	0.000	0.000	26.561
8. Xaisettha	26.636	107.034	0.004	0.000	0.000	133.673
9. Xaithani	4.106	622.814	12.010	92.299	151.497	882.726
						3,995.230

Table 9: Comparison of FAHP-GIS results with World Bank (2021) [4]

Area type	FAHP-GIS results	World Bank (2021) findings
Urban core (Chanthabouly, Xaisettha, Sikhotabong, Sisattanak, Hatxayfong)	Very High–High demand (64.5% of study area)	Water demand increasing 8–10% annually
Peri-urban (Xaithani, Naxaythong)	Medium demand	Water supply capacity expanding only 5% annually
Rural districts (Sangthong, Pakngum)	Low–Very Low demand (36% of study area)	~20% of villages lack piped water access

These findings emphasize that water demand is not solely a function of population growth but also of infrastructural accessibility and spatial development trajectories. Overall, the results confirm that access to piped water and demographic pressure are the most critical determinants of domestic water demand in Vientiane Capital. The FAHP–GIS framework thus offers a practical decision-support tool for policymakers and water authorities. By identifying spatial variations in demand, the model enables targeted investment in piped water systems, equitable resource allocation, and the design of resilient strategies to ensure sustainable water supply under conditions of rapid urbanization and climate variability.

The comparison with World Bank (2021) [4] confirms that the FAHP–GIS model accurately reflects the imbalance between water demand and supply in Vientiane Capital (Table 9). High-demand urban districts correspond to areas where consumption has grown by 8–10% annually, while supply capacity has increased by only 5% per year. Rural districts, where approximately 20% of villages lack piped water, align with the low-demand zones identified in this study. These findings underscore the urgent need for infrastructure investment and equitable resource allocation to address both urban growth and rural water insecurity. The spatial analysis revealed a strong correlation between population density and water demand, with a coefficient of determination ($R^2 = 0.78$). This quantitative evidence supports Objective 1, which aimed to assess demographic influence on water consumption. Furthermore, the integration of socio-economic and land-use factors demonstrated significant explanatory power, aligning with Objective 2. Comparative metrics across districts showed that areas with mixed residential and commercial land use exhibited 25–30% higher demand scores compared to predominantly agricultural zones. These findings highlight the robustness of the FAHP-GIS model in capturing multidimensional drivers of water demand.

3.2 Versification Water Demand

Verification of the water demand analysis was conducted to ensure the reliability and accuracy of the FAHP–GIS model results. The verification process involved two complementary approaches:

1) Comparison with Actual Water Supply Records
    a. Data from the Vientiane Capital Water Supply Authority were used to validate the spatial distribution of demand.
    b. The recorded consumption levels from water treatment plants (Chinaimo, Kaolieo, Dongmarkhay I & II, Dongbang, Thadeua, and Saendin) were compared with the high-demand zones identified in the suitability map.
    c. The results showed strong consistency, as districts classified as high-demand (Chanthabouly, Xaisettha, Sikhotabong, Sisattanak, and Hatxayfong) corresponded to areas with the highest recorded water consumption.

2) Field Survey and Community Feedback (Figure 10)
   a. Household surveys and interviews with local residents and water authority officials were conducted to cross-check the model outputs.
   b. Respondents confirmed that water demand is highest in urbanized districts with dense populations and reliable piped water systems.
   c. In contrast, medium- and low-demand areas (Sangthong, Naxaythong, Xaithani, and Pakngum) reported limited access to piped water, with approximately 20% of villages relying on groundwater. Seasonal droughts, particularly between April and June, further validated the classification of these districts as medium- to low-demand zones.

3) Consistency with Demographic and Socio-Economic Data
   a. Statistical data from the Lao Statistics Bureau were analyzed to verify population density, household size, and socio-economic conditions.
   b. The demographic patterns aligned with the FAHP-derived weights, reinforcing the conclusion that population density and access to piped water are the most influential determinants of domestic water demand.

Figure 10: Field data verification at Vientiane Capital, Lao PDR

Overall, the verification process confirmed that the FAHP–GIS model provides a robust and reliable representation of water demand in Vientiane Capital. The consistency between model outputs, actual consumption records, and field observations demonstrates the validity of the approach. This verification strengthens the applicability of the model as a decision-support tool for policymakers and water authorities, enabling evidence-based planning and sustainable management of urban water resources. To validate the FAHP–GIS model, predicted water demand levels were compared with actual consumption records from the Vientiane Capital Water Supply Authority. Statistical accuracy tests were conducted using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). The results indicated strong agreement, with $R^2 = 0.87$, confirming that the model reliably represents spatial variations in domestic water demand. This validation enhances confidence in the suitability map as a decision-support tool.

4. Conclusions

This study demonstrates the effectiveness of integrating the Fuzzy Analytic Hierarchy Process (FAHP) with Geographic Information System (GIS) in analyzing domestic water demand in Vientiane Capital. The results revealed that access to piped water and population density are the most influential determinants of water demand, while household size, elevation, and distance from water sources exert relatively lower influence. The Water Demand Suitability Map classified the study area into five levels of demand: very high (4.40%), high (60.11%), medium (7.34%), low (8.79%), and very low (19.36%).

Very high- and high-demand areas were concentrated in the urban core districts Chanthabouly, Xaisettha, Sikhotabong, Sisattanak, and Hatxayfong where water treatment plants and efficient piped systems are located, and which also represent the centers of economic activity, trade, and investment. In contrast, medium- to very low-demand areas were found in peripheral districts such as Sangthong, Naxaythong, Xaithani, and Pakngum, where water supply is unevenly distributed, approximately 20% of villages lack piped water access, and seasonal droughts (April–June) exacerbate water scarcity. These findings highlight the spatial disparities between urban and rural communities and underscore the vulnerability of peripheral districts to water insecurity. From a policy perspective, the results emphasize the urgent need to prioritize infrastructure expansion and service coverage in underserved districts, particularly those dependent on groundwater and exposed to drought risk. Policymakers and water authorities should focus on:

- Targeted investment in piped water systems to reduce reliance on groundwater extraction.
- Equitable resource allocation to ensure that marginalized communities gain access to clean water.
- Resilience planning to mitigate seasonal drought impacts through integrated water management strategies.
- Urban growth management to balance water demand between central economic zones and expanding peri-urban areas.

The methodological framework presented here offers a replicable tool for other rapidly urbanizing cities in Southeast Asia. By linking spatial analysis with decision-making, the study provides a strategic basis for sustainable water resource management, ensuring that infrastructure development aligns with demographic pressures, spatial disparities, and climate variability. This study highlights access to piped water and population density as the main drivers of domestic water demand in rapidly urbanizing areas. The FAHP–GIS framework offers a practical tool for identifying priority zones for infrastructure expansion. However, limitations remain, particularly the reliance on expert judgment and the exclusion of climate change projections and future land use dynamics. Future research should integrate scenario-based modeling and machine learning to forecast long-term demand under diverse socio-economic and environmental conditions, and extend the methodology to other urban centers in Lao PDR and Southeast Asia to strengthen regional water management strategies.

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References

[1] Ciampittiello, M., Marchetto, A. and Boggero, A., (2024). Water Resources Management under Climate Change: A Review. *Sustainability*, Vol. 16(9). https://doi.org/10.3390/su16093590.

[2] Asian Development Bank. (2020). *Lao People's Democratic Republic: Water Supply and Sanitation Sector Assessment, Strategy, and Road Map.* Manila: Asian Development Bank. https://www.adb.org

[3] Lao Statistics Bureau. (2020). *Population Census Report: Vientiane Capital.* Vientiane: Lao Statistics Bureau. https://www.lsb.gov.la

[4] World Bank. (2021). *Lao PDR Urban Water Supply and Demand Assessment.* Washington, DC: World Bank. https://www.worldbank.org

[5] Liu, Y., Eckert, C. M. and Earl, C., (2020) A Review of Fuzzy AHP Methods for Decision Making with Subjective Judgements. *Expert System with Applications*, Vol. 161 (113738), 1-30. https://doi.org/10.1016/j.eswa.2020.113738.

[6] Thammaboribal, P., Triapthti, N., & Lipiloet, S. (2025). Using of Analytical Hierarchy Process (AHP) in Disaster Management: A Review of Flooding and Landslide Susceptibility Mapping. *International Journal of Geoinformatics*, Vol. 21(4), 177–196. https://doi.org/10.52939/ijg.v21i4.4091.

[7] Baalousha, H. M., Younes, A., Yassin, M. A. and Fahs, M., (2023) Comparison of the Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Logic for Flood Exposure Risk Assessment in Arid Regions. *Hydrology*, Vol. 10(136), 1-22. https://doi.org/10.3390/hydrology10070136.

[8] Saaty, T. L., (2008). *The Analytic Hierarchy Process: Planning, Priority Setting.* Resource Allocation, Vol. 1, 1-287.

[9] Cikmaz, B. A., Yildirim, E. and Demir, I., (2023) Flood Susceptibility Mapping Using Fuzzy Analytical Hierarchy Process for Cedar Rapids, Iowa. I*nternational Journal of River Basin Management,* Vol. 23, 1-13. https://doi.org/10.1080/15715124.2023.2216936.

[10] Chang, D. Y., (1996) Applications of the Extent Analysis Method on Fuzzy AHP. E*uropean Journal of Operational Research*, Vol. 95(3), 649–655. https://doi.org/10.1016/0377-2217(95)00300-2.

[11] Rezakhani, P., (2012). Fuzzy MCDM Model for Risk Factor Selection in Construction Projects. *Engineering Journal,* Vol. 16(5), 81-93. https://doi.org/10.4186/ej.2012.16.5.79.

[12] Itsarawisut, J. and Laosuwan, T., (2022). Estimation of Particulate Matter Less than 10 Microns Volume through Various Formats of Spatial Interpolation Methods. *Geographia Technica*, Vol. 17(2). https://www.technicalgeography.org/pdf/2_2022/03_itsarawisut.pdf.

[13] Predabmook, P. and Laosuwan, T., (2021). The Integration of Geo-Informatics Technology with Universal Soil Loss Equation to Analyze Areas Prone to Soil Erosion in Nan Province. *ARPN Journal of Engineering and Applied Sciences,* Vol. 16(8), 823-830.

[14] Wijitkosum, S. and Sriburi, T., (2019) Fuzzy AHP Integrated with GIS Analyses for Drought Risk Assessment: A Case Study from Upper Phetchaburi River Basin, Thailand. *Water*, Vol. 11(5), 939-955. https://doi.org/10.3390/w11050939.

[15] Yazawa, T., Morita, A. and Shimizu, T., (2023) Assessment of Basin-scale Water Stress using Geographic Information System in Southeast Asian Countries with Megacities. *The Journal of Indonesia Sustainable Development Planning*, Vol. 4(1), 1-20. https://doi.org/10.46456/jisdep.v4i1.383.

[16] Ong, C., Tortajada, C. and Arora O., (2023). *Urban Water Demand Management in ASEAN: Policy and Practice.* ASEAN Development Studies.

[17] Putra, M. S. D., Andryana, S., Fauziah, K. and Gunaryati, A., (2018). Fuzzy Analytical Hierarchy Process Method to Determine the Quality of Gemstones. *Advance in Fuzzy System*, Vol. 1-6. https://doi.org/10.1155/2018/9094380.

[18] Hategekimana, Y., Yu, L., Nie, Y., Zhu, J., Liu, F. and Guo F., (2018) Integration of Multi-Parametric Fuzzy Analytic Hierarchy Process and GIS along the UNESCO World Heritage: A Flood Hazard Index, Mombasa Country, Kenya. *Natural Hazards*, Vol. 92(2), 1137-1153. https://doi.org/10.1007/s11069-018-3244-9.

[19] Emrouznejad, A. and Ho, W., (2018). *Fuzzy Analytic Hierarchy Process.* Boca Raton, Florida. CRC Press.

[20] Yang, X., Ding, J. and Hou, H., (2013) Application of a Triangular Fuzzy AHP Approach for Flood Risk Evaluation and Response Measures Analysis. *Natural Hazards*, Vol. 68, 657-674. http://dx.doi.org/10.1007/s11069-013-0642-x.

[21] Peng, G., Han, L., Liu, Z., Guo, Y., Yan, J. and Jia, X., (2021) An Application of Fuzzy Analytic Hierarchy Process in Risk Evaluation Model. *Frontiers in Psychology*, Vol. 12, 1-12. https://doi.org/10.3389/fpsyg.2021.715003.

[22] Gigovic', L., Pamučar, D., Bajic', Z. and Drobnjak, S., (2017) Application of GIS-Interval rough AHP Methodology for Flood Mapping in Urban Areas. *Water*, Vol. 9(360), 1-26. https://doi.org/10.3390/w9060360.

[23] Pawattana, C., Jeefoo, P., Vansarochana, C. and Poopiwkham, S., (2026). Development of Flood Risk Maps using an Integrated Hydrodynamic Model and FAHP in the Lower Nam Phong Basin, Thailand. *Geographia Technica*, Vol. 21(1), 306-322. https://doi.org/10.21163/gt_2026.211.20.

[24] Parsian, S., Amani, M., Moghimi, A., Ghorbanian, A. and Mahdavi, S., (2021) Flood Hazard Mapping Using Fuzzy Logic, Analytical Hierarchy Process, and Multi-Source Geospatial Datasets. *Remote Sensing,* Vol. 13(23), 4761-4783. https://doi.org/10.3390/rs13234761.

[25] Yodying, A., Mahavik, N., Tantanee, S., Kongmuang, C., Keteku, A. K., Chidburee P, Seejata, K. and Chatsudarat, S., (2022). A Fuzzy AHP Approach to Assess Flood Hazard for Area of Bang Rakam Model 60 Project in Yom River Basin, Northern Thailand. *Applied Environmental Research*, Vol. 44(1), 108-125. https://doi.org/10.35762/AER.2021.44.1.9.

[26] Vojinovic, Z., Hammond, M., Golub, D., Hirunsalee, S., Weesakul, S., Meesuk, V., Medina, N., Sanchez, A., Kumara, S. and Abbott, M., (2016). Holistic Approach to Flood Risk Assessment in Areas with Cultural Heritage: A Practical Application in Ayutthaya, Thailand. *Natural Hazards,* Vol. 81, 589-616. https://doi.org/10.1007/s11069-015-2098-7.