

Article

Diagnosing the Factors of Domestic Water Shortage Under Climate Change Through an XGBoost-SHAP Framework

Wonjin Kim, Sijung Choi *, Seongkyu Kang and Soyoung Woo

Department of Hydro Science and Engineering Research, Korea Institute of Civil Engineering and Building Technology, Goyang-si 10223, Republic of Korea; wjkim@kict.re.kr (W.K.); skkang@kict.re.kr (S.K.); wsy0209@kict.re.kr (S.W.)

* Correspondence: sjchoi@kict.re.kr

Abstract

Climate-change-induced drought can increase domestic water shortage not only by reducing runoff but also by exposing weaknesses in local sources, reservoirs, and wide-area transfer networks. This study simulates domestic water shortage in the Seomjin River water system, South Korea, using the Korea-Water Evaluation and Planning system (K-WEAP), and proposes an integrated eXtreme Gradient Boosting (XGBoost)–Shapley Additive exPlanations (SHAP) framework to diagnose the explanatory factors of the simulated shortage. Representative drought scenarios were selected from an ensemble of climate projections using a dryness score based on precipitation-related extreme climate indices. K-WEAP was used to simulate shortage for eleven administrative districts, and XGBoost (version 3.2.0) models were trained for districts with sufficient shortage samples. SHAP analysis and shortage-event clustering were then applied to identify dominant explanatory factors and recurrent shortage patterns. The XGBoost models reproduced the simulated shortage rates well, with test R^2 values exceeding 0.91. Wide-area water supply was the dominant explanatory factor in three inland districts, whereas reservoir supply was more influential in the southern coastal district. The dependence analysis revealed threshold-type responses, in which shortage risk increased sharply once key supply variables fell below district-specific critical ranges. The results indicate that domestic water shortage is governed by district-specific supply pathways and threshold-type system responses rather than by uniform basin-wide drought effects.

Keywords: domestic water shortage; climate change; K-WEAP; XGBoost; SHAP

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1. Introduction

Climate change is reshaping the hydrological cycle by altering the magnitude, timing, and variability of precipitation, evapotranspiration, and runoff. These changes challenge the assumption of hydrological stationarity—that the statistical properties of hydroclimatic variables remain constant over time—which has traditionally underpinned water resources planning [1]. In particular, climate change can alter water availability and exacerbate mismatches between water supply and demand under changing climatic and socioeconomic conditions [2–4]. Such impacts are especially concerning in monsoon-dominated regions, where a large share of annual runoff is concentrated within a few months and year-round supply depends heavily on reservoir storage and wide-area water transfer infrastructure [5]. South Korea is a representative case: roughly two-thirds of annual

precipitation falls during the summer monsoon, while municipal supply relies substantially on multi-purpose dams and wide-area waterworks sensitive to seasonal inflow changes [6]. Evaluating domestic water supply reliability under these conditions therefore requires a framework that jointly accounts for hydro-climatic variability and the structural characteristics of water supply systems.

Scenario-based water resources models have been widely used to evaluate supply reliability, unmet demand, and adaptation options under changing conditions. Among available platforms, the Water Evaluation and Planning system (WEAP) is well suited to the present study because of its demand–priority-driven allocation logic, flexible link–node structure, and transparent scenario management framework [7]. WEAP has been applied to assess water availability and management alternatives under changing hydro-climatic conditions [8], agricultural and urban water allocation [9], and unmet demand under combined climatic and socio-economic pressures [10]. Its link–node architecture can also represent the hierarchical supply structure of South Korea’s water system, where wide-area waterworks, local waterworks, and direct source abstractions coexist within a single district. These features make WEAP appropriate for simulating domestic water shortage rates at the district scale under multiple climate change scenarios.

Many previous studies have focused on quantifying water-supply risks under alternative scenarios [11], while a smaller number have explicitly diagnosed the causes of water scarcity and linked them to potential management actions [12]. At the district scale, water-supply vulnerability is influenced not only by regional water availability but also by source dependence and the resilience of the connected supply infrastructure [13,14]. Even under identical climate forcing, the dominant drivers of shortage can differ markedly among districts. Scenario-based simulation alone, while essential for quantifying shortages, cannot reveal this underlying factor structure. An analytical approach capable of learning and interpreting the nonlinear relationships between shortage rates and their explanatory variables is therefore needed.

Machine learning methods offer a complementary approach for identifying such relationships in complex hydro-infrastructure datasets. XGBoost, a regularized gradient tree boosting algorithm, can effectively capture nonlinear responses, threshold effects, and variable interactions while controlling model complexity [15–17]. These properties are well suited to analyzing domestic water shortage rates, which may arise from nonlinear combinations of supply volumes, reservoir storage, demand conditions, and operational constraints. In the water resources domain, XGBoost has been applied to drought prediction, water quality forecasting, and flood susceptibility mapping [18–20], yet its application to diagnosing the factors governing domestic water supply shortage remains unexplored. Moreover, the limited interpretability of ensemble learning models can be addressed through SHAP, a framework that decomposes predictions into feature-level contributions based on Shapley values [21]. In particular, TreeSHAP enables efficient and consistent interpretation of tree-based models, revealing both global feature importance and local directional effects [22]. The combination of XGBoost and SHAP thus provides a means not only to reproduce simulated shortage responses but also to interpret the dominant factors driving district-level shortage variability.

This study proposes an integrated XGBoost–SHAP framework to diagnose the explanatory factors associated with domestic water shortage across administrative districts under representative drought scenarios. K-WEAP is first used to simulate district-level domestic water shortage rates, and district-specific XGBoost regression models are then developed to capture nonlinear relationships between shortage rates and supply- and storage-related variables. SHAP analysis is subsequently applied to interpret the contribution of each variable and identify the dominant factors controlling water shortage in

each district. Although K-WEAP, XGBoost, SHAP, and clustering are individually established methods, their combination addresses a gap that none of them resolves alone: scenario-based models can quantify shortage but do not explain which supply components govern its variation, while machine learning and SHAP have been applied to drought prediction and water quality forecasting but not to diagnosing simulated water supply–demand imbalances at the district scale. By using XGBoost as a surrogate of the K-WEAP simulation and SHAP as an interpretive layer, this framework decomposes complex shortage responses into variable-level contributions, revealing district-specific supply pathways, threshold-type system behavior, and recurrent shortage-event patterns that conventional scenario comparison cannot identify.

2. Materials and Methods

2.1. Study Area

2.1.1. Overview

The study area of this research is the Seomjin River basin, located in the southern part of the Korean Peninsula. As shown in Figure 1, the left panel presents the regional location of the basin within South Korea, while the right panel provides an enlarged view of the study area, including the basin boundary, major river networks, dam and reservoir facilities, and administrative districts selected for analysis. The Seomjin River basin extends across parts of Jeolla-bukdo, Jeolla-namdo, and Gyeongsangnam-do. The main stream of the Seomjin River flows through the central part of the basin, and major tributaries, including the Boseong River, are connected to the river system. The basin is surrounded by neighboring river systems, including the Geum River, Dongjin River, Yeongsan River, and Nakdong River basins. This geographical setting indicates that the Seomjin River basin is hydrologically connected to surrounding regions and has an important role in regional water management. The study area includes tributary catchments, agricultural areas, and downstream administrative districts with domestic and industrial water demands. These spatial characteristics make the basin suitable for examining water supply mechanisms under changing hydrological conditions. In particular, the coexistence of natural river systems, dam-regulated flows, and administratively defined demand areas provides an appropriate basis for evaluating spatially heterogeneous water supply risks.

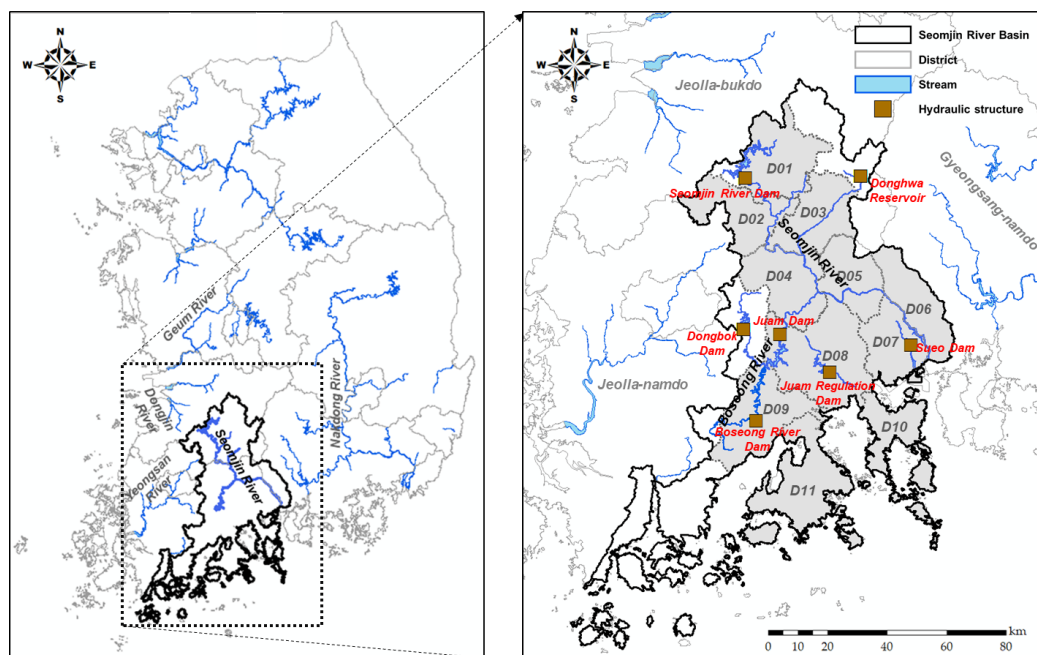


Figure 1. Description of study area. The area codes D01–D11 correspond to the districts described in Table 1.

2.1.2. Resolution and Supply System

In this study, eleven administrative districts were selected as the spatial units of analysis and denoted as D01–D11 (Table 1). These districts are located within the Seomjin River basin and are associated with the river system through water intake, reservoir operation, local water use, and wide-area water supply connections. The spatial resolution was therefore defined at the administrative-district scale rather than at the sub-basin scale alone, allowing domestic water supply to be evaluated in relation to both hydrological conditions and district-level water management characteristics.

The Seomjin River basin has a complex water supply structure composed of multi-purpose dams, reservoirs, tributary systems, local water sources, and wide-area transmission networks. Major water infrastructure includes Seomjin River Dam, Juam Dam, Juam Regulation Dam, Boseong River Dam, Dongbok Dam, Sueo Dam, and Donghwa Reservoir. These facilities are distributed across the Seomjin River, Yocheon River, and Boseong River systems and support water storage, regulation, and allocation across the selected administrative districts.

Because of this configuration, domestic water shortage in the study area is influenced not only by natural runoff variability but also by reservoir storage, dam operation, intake and conveyance capacity, wide-area water supply allocation, and district-level differences in demand structure and source dependence. In particular, each administrative district relies on a distinct combination of wide-area waterworks, local waterworks, and groundwater, resulting in spatially heterogeneous supply conditions even under the same climate forcing.

Table 1. Administrative districts in the Seomjin River water system.

District ID	District Name	Province
D01	Imsil-gun	Jeolla-bukdo
D02	Sunchang-gun	Jeolla-bukdo
D03	Namwon-si	Jeolla-bukdo
D04	Gokseong-gun	Jeolla-namdo
D05	Gurye-gun	Jeolla-namdo
D06	Hadong-gun	Gyeongsang-namdo
D07	Gwangyang-si	Jeolla-namdo
D08	Suncheon-si	Jeolla-namdo
D09	Boseong-gun	Jeolla-namdo
D10	Yeosu-si	Jeolla-namdo
D11	Goheung-gun	Jeolla-namdo

2.2. Water Supply–Demand Simulation Model

2.2.1. Model Configuration

The K-WEAP model was used to simulate the water supply–demand balance of the Seomjin River water system and to estimate domestic water shortage in the study area. K-WEAP is a Korean water resources planning model based on the WEAP framework, representing a water resources system as a network of river reaches, reservoirs, demand sites, transmission links, return flows, and operating rules. The model domain included the Seomjin River basin and its connected wide-area water supply network, including major rivers, tributaries, reservoirs, dams, intake facilities, demand sites, and transmission links. This configuration was designed to represent both natural hydrological connectivity and engineered water transfers among supply sources and demand districts.

The simulation was conducted at a pentadic time step, with each month divided into six periods (72 time steps per year). The simulation period covered 2011–2100, consistent with the time horizon of the climate change scenarios. Natural runoff simulated by Soil and Water Assessment Tool (SWAT) under climate change conditions was used as hydrological input for river reaches and reservoir inflow nodes. Reservoirs and dams were parameterized using storage characteristics, inflow, release, and operational constraints, while demand sites were connected to local and wide-area water sources based on the actual supply network.

Water allocation was simulated according to predefined demand priorities and supply preferences. Domestic and industrial water demands were assigned the highest priority, followed by agricultural water demand and instream flow requirements. When available supply was insufficient to meet demand, K-WEAP estimated unmet demand for each demand site and time step. Domestic water shortage was then evaluated using the shortage rate derived from unmet domestic demand and total domestic demand.

The configured model was checked against available water supply-system records, including reservoir storage, releases, and supply volumes where data were available. Calibration against observed streamflow at five gauging stations yielded R^2 values ranging from 0.71 to 0.91 and PBIAS values within $\pm 2.5\%$, indicating that the model adequately reproduced the observed flow regime across the basin. Detailed calibration results are provided in Figure S1.

2.2.2. Climate Change Scenarios

Future hydroclimatic conditions were constructed from Coupled Model Intercomparison Project Phase 6 (CMIP6) to assess domestic water shortage under drought-prone conditions. In this study, 15 global climate models and four Shared Socioeconomic Pathways (SSPs), SSP1, SSP2, SSP3, and SSP5, were considered as the initial climate projection ensemble. The climate variables required for SWAT, including precipitation, maximum and minimum temperature, relative humidity, wind speed, and solar radiation, were prepared from each climate projection. SWAT-simulated runoff was then used as hydrological input for the K-WEAP simulation.

Representative drought scenarios were selected from the CMIP6 ensemble using a dryness score derived from precipitation-related indices of Expert Team on Climate Change Detection and Indices. These indices characterize precipitation amount, intensity, frequency, and persistence, which are directly related to meteorological dryness and drought development. For each climate projection, the indices were calculated over the target basin and converted into a dryness score, with higher values indicating stronger drought-prone characteristics.

Based on the dryness score ranking, three representative drought scenarios were selected for the simulation. Simulating all 60 projections through both SWAT and K-WEAP at pentadic resolution for the period 2011–2100 would require substantial computational resources, and the diagnostic framework—including district-specific XGBoost training, SHAP analysis, and shortage-event clustering—would need to be repeated for each scenario set. The use of three top-ranked scenarios therefore allowed the analysis to focus on the most drought-prone conditions while keeping the diagnostic workflow tractable. The calculation procedure, ranking of climate projections, and selected scenarios are summarized in Figure S2.

2.3. Diagnostic Framework for Explanatory Factor Analysis

2.3.1. Construction of XGBoost-SHAP Input Variables

Input data for the XGBoost-SHAP analysis were prepared from the K-WEAP simulation outputs to diagnose the explanatory factors of domestic water shortage. The dataset was constructed separately for each administrative district because the selected districts differ in water source composition, supply pathways, and reservoir connectivity. This structure was used to retain the characteristics of each local water supply system rather than applying a single basin-wide explanatory dataset.

While each dataset was organized at the pentadic time scale, the response variable was defined as the domestic water shortage rate, calculated from unmet domestic water demand and total domestic water demand. This variable was used as the dependent variable in the XGBoost regression models.

The explanatory variables were selected to represent the main supply and storage conditions affecting domestic water availability. As summarized in Table 2, the input variables included local water supply, wide-area water supply, groundwater supply, reservoir supply, direct river intake, storage of connected reservoirs and multipurpose dams, and month of year. The supply-related variables represent the amount of water delivered from each source, whereas the storage variables describe the available stored water in major facilities connected to the supply system. Month was included to account for seasonal variation in water availability and demand conditions.

A common input-variable structure was defined to ensure consistency across administrative districts. However, the actual values assigned to each variable reflected the water supply network connected to each district. Variables corresponding to unavailable or non-connected sources were assigned zero values when necessary. Therefore, the prepared input data preserved differences in source dependence, infrastructure connectivity, and storage-related constraints among administrative districts. These datasets were subsequently used for XGBoost regression and SHAP-based interpretation to identify the dominant explanatory factors associated with domestic water shortage. In addition, multicollinearity among the explanatory variables was assessed using the Variance Inflation Factor (VIF). All VIF values remained below 4.0 for every district (Table S1), indicating that multicollinearity did not substantially affect the stability of the subsequent XGBoost models or the reliability of the SHAP-based interpretation.

Table 2. Explanatory variables used for XGBoost-SHAP analysis.

Variable	Description	Unit
Y	Domestic water shortage rate	%
X _a	Local water supply	m ³
X _b	Wide-area water supply	m ³
X _c	Groundwater supply	m ³
X _d	Reservoir supply	m ³
X _e	Direct river intake	m ³
X _{s,1}	Storage of Donghwa Reservoir	m ³
X _{s,2}	Storage of Seomjin River Dam	m ³
X _{s,3}	Storage of Juam Dam	m ³
Month	Month of year	-

2.3.2. XGBoost Regression Model

XGBoost is a gradient boosting algorithm that combines multiple regression trees into an additive ensemble. Each tree is sequentially added to correct the residual errors of the previous ensemble, allowing the model to capture nonlinear relationships and interactions among explanatory variables. This capability has recently been applied to diagnose divergent hydrological responses to multiple controlling factors in complex environmental systems [23]. This property is useful for diagnosing domestic water shortage mechanisms because shortage occurrence may respond nonlinearly to changes in water supply, reservoir storage, and seasonal conditions.

For each sample i , the XGBoost prediction is expressed as

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in F \quad (1)$$

where i denotes an individual sample corresponding to a pentadic time step; $\hat{y}_i$ is the predicted water shortage rate for sample i ; x_i is the vector of explanatory variables for sample i ; K is the total number of regression trees; k is the index of an individual tree; f_k is the k -th regression tree; and F is the function space of regression trees.

The model is estimated by minimizing an objective function consisting of a prediction loss term and a regularization term:

$$L = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (2)$$

where L is the objective function; n is the number of samples; y_i is the simulated domestic water shortage rates for sample i ; $l(y_i, \hat{y}_i)$ is the loss function measuring the prediction error; and $\Omega(f_k)$ is the regularization term that penalizes the complexity of the k -th tree. Through this formulation, XGBoost improves predictive performance while controlling overfitting. The trained XGBoost models were subsequently used for SHAP-based interpretation to evaluate the contribution of each explanatory variable to domestic water shortage.

For each district, the dataset was split into training and testing subsets at a 70:30 ratio using a chronological split within each drought scenario to preserve temporal structure. Features with uniformly zero values were excluded per district. The XGBoost models were configured with 1000 estimators, a maximum tree depth of 3, a learning rate of 0.01, and a squared-error objective function. Overfitting was controlled through row and column subsampling ratios of 0.8, shallow tree depth, and the default L2 regularization of XGBoost. These settings were held constant across all districts to ensure consistency in the diagnostic framework. Systematic hyperparameter tuning was not performed because the primary objective of the XGBoost models is not predictive optimization but surrogate-based decomposition through SHAP; for this purpose, stable and generalizable configurations were prioritized over district-specific performance maximization.

2.3.3. SHAP-Based Interpretation

SHAP-based interpretation was applied to the trained XGBoost models to diagnose the explanatory factors of domestic water shortage. SHAP is an additive feature attribution method based on Shapley values from cooperative game theory [24]. Although XGBoost can capture nonlinear relationships between shortage rates and explanatory variables, its ensemble structure does not directly indicate how individual predictors contribute to each prediction. SHAP was therefore used to decompose model outputs into variable-level contributions and to provide an interpretable explanation of the trained regression models.

For each sample i , the XGBoost prediction can be expressed using SHAP values as

$$\hat{y}_i = \phi_0 + \sum_{j=1}^M \phi_{i,j} \quad (3)$$

where ϕ_0 is the baseline prediction, defined as the expected model output over the training dataset; M is the number of explanatory variables; j is the index of an explanatory variable; and $\phi_{i,j}$ is the SHAP value of variable j for sample i . A positive SHAP value indicates that the corresponding variable increases the predicted shortage rate relative to the baseline prediction, whereas a negative SHAP value indicates that it decreases the predicted shortage rate.

SHAP values were calculated separately for each administrative district. The mean absolute SHAP value was used to evaluate the relative importance of explanatory variables, while the sign and distribution of SHAP values were used to interpret whether each variable contributed to increasing or decreasing domestic water shortage. This interpretation enabled the identification of different shortage mechanisms associated with supply composition, source dependence, reservoir storage, and seasonal conditions. The SHAP-based analysis provided an explanatory framework for interpreting the XGBoost results and identifying the dominant factors associated with domestic water shortage under representative drought scenarios.

2.3.4. Shortage-Event Clustering and Classification

Shortage-event clustering was conducted to classify domestic water shortage events according to their temporal and severity characteristics. A shortage event was defined as a continuous period in which the K-WEAP-simulated domestic water shortage rate was greater than zero. Events were extracted separately for each administrative district and drought scenario to avoid mixing independent shortage sequences.

For each event, five descriptors were calculated (Table 3): duration, mean shortage rate, maximum shortage rate, cumulative shortage rate, and peak month. These variables were selected to represent shortage persistence, average severity, peak intensity, cumulative burden, and seasonal timing. Before clustering, the event descriptors were standardized to remove the influence of different variable scales.

K-means clustering was applied to group shortage events with similar characteristics [25,26]. Candidate cluster numbers were evaluated using the silhouette score and Davies–Bouldin index, which measure cluster cohesion and separation from different perspectives [27,28]. Based on the clustering diagnostics and interpretability of event characteristics, four shortage-event types were used for the final classification: short low-intensity, long low-intensity, short extreme, and long severe-cumulative events.

After clustering, the occurrence probability of each shortage-event type was calculated for each administrative district. In addition, event-level SHAP information was linked to the clustered events by averaging the absolute SHAP values over the duration of each event. For each cluster, the event-averaged absolute SHAP values were then aggregated across all events within the cluster, and the relative contribution of each explanatory variable was expressed as its proportion of the total mean absolute SHAP value. This procedure allowed each shortage-event type to be interpreted not only by its temporal shortage characteristics but also by the dominant explanatory factors identified from the XGBoost-SHAP analysis.

Table 3. Variables used for clustering shortage event.

Variable	Description	Interpretation
Duration	Number of consecutive pentadic time steps with shortage	Persistence of shortage
Mean shortage rate	Average shortage rate during the event	Average severity
Maximum shortage rate	Highest shortage rate during the event	Peak intensity
Cumulative shortage rate	Sum of shortage rates over the event duration	Cumulative burden
Peak month	Month in which the maximum shortage occurred	Seasonal timing

3. Results and Discussion

3.1. Domestic Water Shortage Under Representative Drought Scenarios

Domestic water shortage under the representative drought scenarios was evaluated from the K-WEAP simulation outputs. For each administrative district, shortage volume was defined as unmet domestic water demand, and the shortage rate was calculated by dividing shortage volume by total domestic demand.

Table 4 summarizes five indicators of domestic water shortage: failure frequency, mean shortage, mean shortage rate, mean shortage during failure periods, and mean shortage rate during failure periods. Failure frequency represents the percentage of time steps with nonzero shortage, whereas the failure-period indicators were calculated only for time steps in which shortage occurred. Thus, the table distinguishes between how often shortage occurred and how severe the shortage became once the system failed.

The results reveal a strong spatial contrast in shortage behavior. D02, D03, and D04 showed relatively frequent shortage occurrence and high full-period shortage rates, indicating persistent vulnerability under drought conditions. In contrast, D05, D08, and D10 exhibited very low failure frequencies but substantial failure-period shortage intensities, suggesting rare but severe supply failures. D01, D06, D07, and D09 showed no domestic water shortage under the selected drought scenarios.

This contrast is important because average shortage alone can hide operationally critical failures. Persistent shortage implies chronic stress requiring structural supply reinforcement or demand-side management, whereas episodic shortage indicates sensitivity to short-term operational thresholds and may require emergency supply measures [29]. Therefore, shortage frequency and failure-period intensity provide complementary evidence for diagnosing water supply vulnerability.

Overall, domestic water shortage in the Seomjin River water system cannot be interpreted as a uniform response to meteorological drought. The same drought forcing produced different shortage responses depending on local source availability, wide-area transfer dependence, alternative supply options, and storage-related constraints [30]. Based on these results, the subsequent XGBoost-SHAP analysis focused on D02, D03, D04, and D11, where shortage events occurred with sufficient frequency for reliable model training and interpretation. Districts with no or extremely sparse shortage occurrence were excluded from explanatory modeling because their shortage samples were insufficient for robust diagnosis.

Table 4. Characteristics of domestic water shortage by administrative district under representative drought scenarios.

ID	Failure Frequency (%)	Mean Shortage (m ³)	Mean Shortage Rate (%)	Mean Failure Shortage (m ³)	Mean Failure Shortage (%)
D01	0.00	0.00	0.00	0.00	0.00
D02	26.64	1213.29	4.36	3585.11	12.88
D03	30.25	6993.92	6.64	20,659.74	19.62

D04	28.70	1831.40	7.93	5411.52	23.43
D05	0.08	11.94	0.05	14,511.16	64.68
D06	0.00	0.00	0.00	0.00	0.00
D07	0.00	0.00	0.00	0.00	0.00
D08	0.19	46.30	0.01	24,327.40	6.83
D09	0.00	0.00	0.00	0.00	0.00
D10	0.19	26.79	0.01	14,464.78	5.23
D11	4.16	264.01	0.60	6344.19	14.37

3.2. Predictive Performance of XGBoost Models

To assess how well the district-specific XGBoost models captured the K-WEAP-simulated shortage responses, predicted and simulated domestic water shortage rates were compared across the selected districts (Figure 2). Most samples clustered tightly around the 1:1 reference line, particularly in the low-to-moderate shortage range where the majority of observations were concentrated.

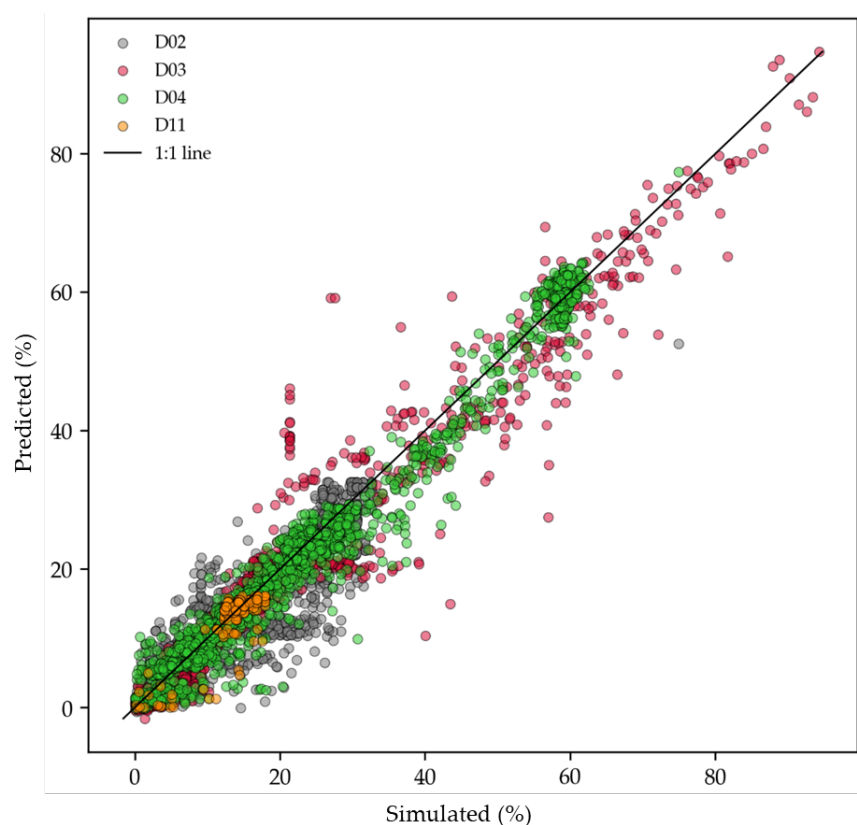


Figure 2. Comparison between K-WEAP-simulated and XGBoost-predicted domestic water shortage rates for the selected districts.

The performance statistics in Table 5 confirm this agreement quantitatively. All districts achieved test R^2 values above 0.91, accompanied by low Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values. D04 and D11 yielded the highest predictive accuracy, whereas D02 exhibited slightly greater scatter and a lower test R^2 . Even so, the overall error magnitudes remained small, suggesting stable model performance across different shortage conditions.

In the high-shortage range, however, several extreme cases were underpredicted, with points deviating noticeably from the 1:1 line. This tendency reflects the scarcity of

high-intensity shortage samples in the training data, which limits the information available for the model to learn extreme response structures. Such behavior is common in tree-based ensemble models when rare events constitute a small fraction of the training set.

Taken together, the trained XGBoost models provide a reliable surrogate of the K-WEAP-simulated shortage rates and form a sound basis for the subsequent SHAP-based interpretation. The time series of simulated and predicted shortage rates for each district and drought scenario are provided in Figure S3. However, the XGBoost models were trained on K-WEAP simulation outputs rather than on observed shortage records. This design reflects the fact that district-level domestic water shortage data at pentadic resolution are not available from operational monitoring systems, making observation-based training infeasible at the spatial and temporal scales considered here. The XGBoost models therefore function as surrogate representations of the K-WEAP system, and the role of SHAP is to decompose these surrogates into variable-level contributions, revealing the explanatory structure embedded in the simulation. The validity of the diagnostic results depends on the fidelity of the K-WEAP model to the actual water supply system, which is supported by calibration and validation against observed streamflow records (Figure S1). While this surrogate-based approach cannot replace direct validation against observed shortage events, it provides an interpretive capability that neither the simulation model nor observational analysis alone can offer [31]. Accordingly, SHAP results for districts or periods where extreme shortage responses are rare should be interpreted alongside the model performance and shortage-event characteristics discussed above.

Table 5. Predictive performance of district-specific XGBoost models for domestic water shortage.

ID	District	Train			Test		
		R ²	RMSE (%)	MAE (%)	R ²	RMSE (%)	MAE (%)
D02	Sunchang-gun	0.929	2.367	1.156	0.913	2.423	1.172
D03	Namwon-si	0.978	2.047	0.896	0.967	2.364	0.982
D04	Gokseong-gun	0.984	1.931	1.053	0.983	2.007	1.102
D11	Goheung-gun	0.985	0.365	0.091	0.976	0.437	0.094

3.3. SHAP-Based Identification of Explanatory Factors

The mean absolute SHAP value represents the average magnitude of each variable's contribution to the predicted domestic water shortage rate, regardless of whether the contribution is positive or negative. Because the model output was expressed as a shortage rate, the SHAP values have the same unit as the model output, i.e., percentage points. Therefore, a larger mean absolute SHAP value indicates a greater influence on model predictions, but does not indicate whether the variable increases or decreases the shortage rate. Figure 3 summarizes the mean absolute SHAP values for the selected districts and shows clear district-specific differences in the relative importance of the explanatory variables.

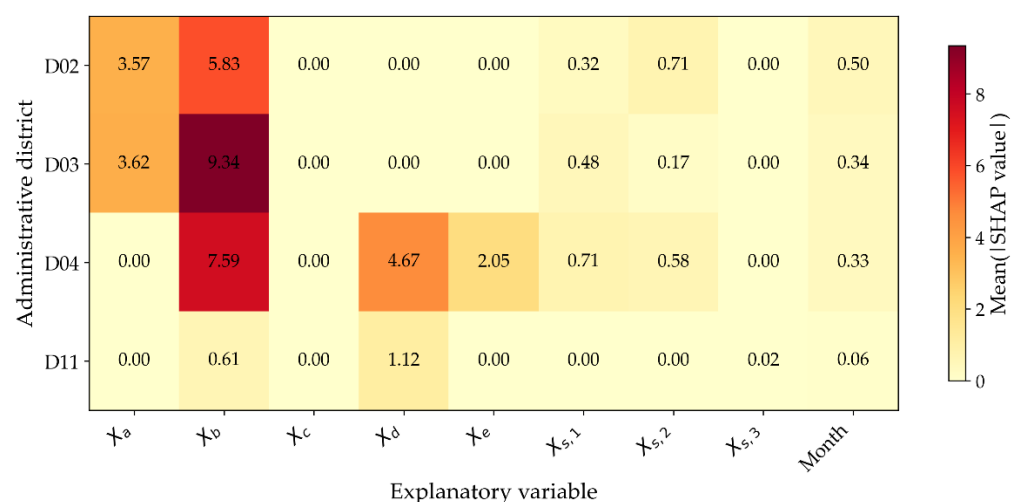


Figure 3. Mean absolute SHAP values of explanatory variables.

Wide-area water supply (X_b) was the most influential variable in D02, D03, and D04. Its importance was especially pronounced in D03, where the SHAP magnitude was clearly higher than that of the other variables. In D02 and D03, local water supply (X_a) also contributed substantially, indicating that shortage prediction in these districts depended on the combined behavior of wide-area and local supply sources. D04 showed a broader explanatory structure: in addition to (X_b), reservoir supply (X_d) and direct river intake (X_e) had notable effects, suggesting that shortage development in this district was linked to multiple supply pathways.

D11 formed a separate case. The magnitude of SHAP values was generally smaller, but reservoir supply emerged as the leading explanatory variable. This pattern indicates that shortage prediction in D11 was more closely tied to reservoir-based supply conditions than to the wide-area supply signal that dominated the other districts. By contrast, groundwater supply, storage variables, and month contributed only weakly in most districts, implying that their direct influence on the predicted shortage rate was limited in the trained models.

The heatmap therefore suggests two broad explanatory patterns: districts in which wide-area water supply was the primary contributor, represented mainly by D02, D03, and D04, and a district in which reservoir supply played a relatively larger role, represented by D11. This distinction provides a clear basis for the following dependence analysis, where the direction and nonlinear behavior of the dominant variables are examined in more detail.

SHAP beeswarm plots were used to examine the direction and distribution of variable effects for each district (Figure 4). Unlike the SHAP importance heatmap, which shows only the magnitude of variable importance, the beeswarm plots indicate whether high or low values of each variable increase or decrease the predicted domestic water shortage rate.

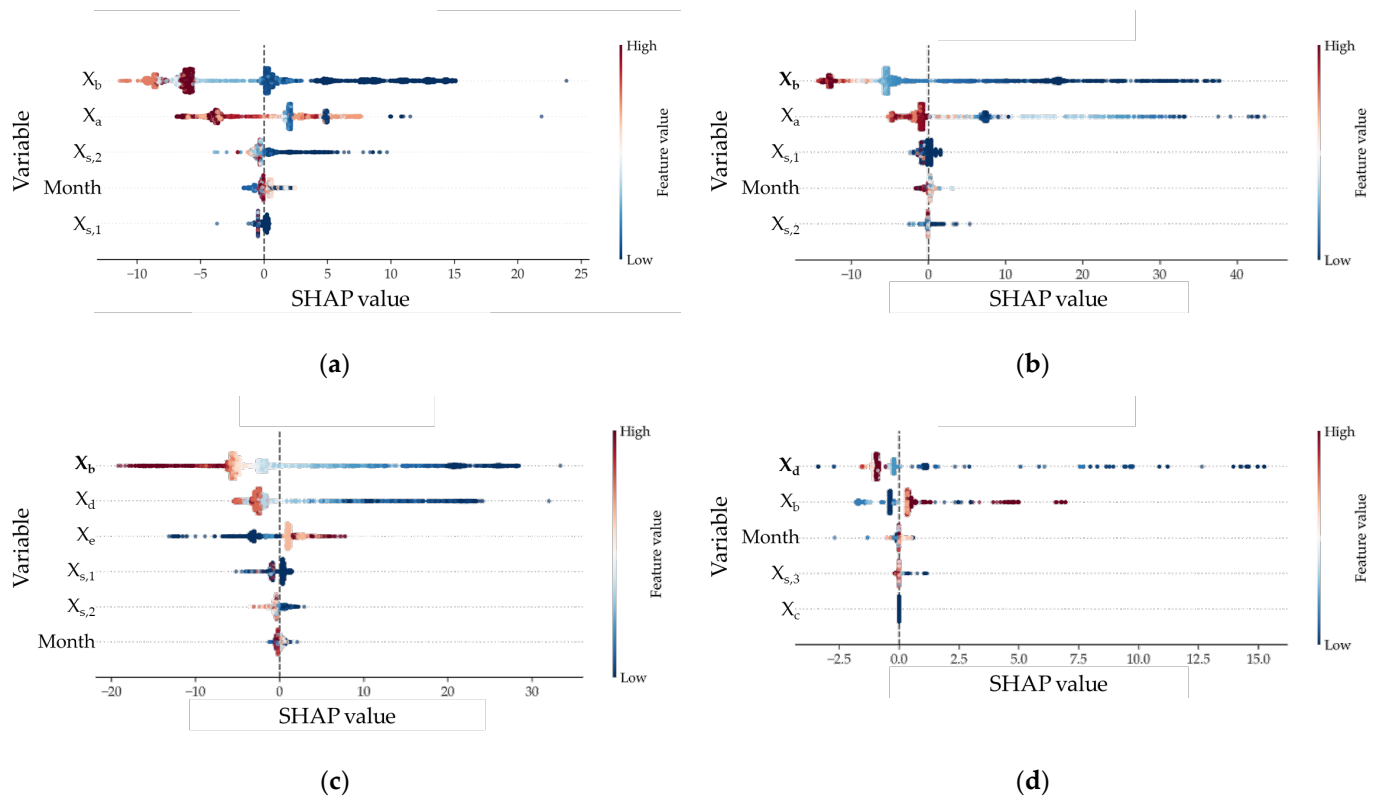


Figure 4. SHAP beeswarm plots showing the direction and distribution of explanatory variable effects: (a) D02, (b) D03, (c) D04, and (d) D11.

D02 and D03 showed clear supply-limitation patterns. In both districts, low wide-area water supply values were associated with positive SHAP values, indicating an increase in the predicted shortage rate, whereas high wide-area water supply values generally reduced the prediction. Local water supply showed a similar but weaker pattern, suggesting that shortage responses in these districts were mainly explained by reductions in wide-area and local supply availability.

D04 exhibited a more mixed explanatory structure. Wide-area water supply remained the dominant factor, but reservoir supply and direct river intake also showed noticeable contributions. Low wide-area water supply and low reservoir supply were linked to higher predicted shortage rates. In contrast, high direct river intake values appeared on the positive SHAP side, which is more likely to reflect increased intake as an operational response during stressed conditions rather than direct causation of shortage.

D11 showed a distinct reservoir-related pattern. Low reservoir supply values were associated with positive SHAP values, indicating higher predicted shortage rates when reservoir-based supply was reduced. Wide-area water supply showed a less monotonic response, suggesting that it may partly represent compensatory supply behavior during shortage periods.

These beeswarm patterns suggest three broad tendencies in shortage response: D02 and D03 showed characteristics consistent with supply limitation, D04 exhibited a more mixed explanatory structure involving multiple supply pathways, and D11 displayed a pattern more closely associated with reservoir supply conditions. This result also shows why SHAP values should be interpreted with reference to the actual water supply system rather than treated as simple causal effects.

The SHAP dependence plots reveal that the dominant variables did not affect domestic water shortage in a gradual or linear manner (Figure 5). Instead, most variables showed threshold-type behavior: below certain supply levels, their SHAP values became strongly

positive, increasing the predicted shortage rate; above those ranges, their effects rapidly weakened or shifted to shortage-reducing contributions.

This pattern was most evident in D02 and D03. Wide-area and local water supply both acted as direct limiting factors, with low supply values sharply increasing the predicted shortage rate. D03 showed the steepest response, indicating that its shortage prediction was highly sensitive to supply reduction. In these districts, the message is straightforward: once available supply falls below a critical range, shortage risk rises quickly.

D04 showed a broader mechanism. Wide-area water supply and reservoir supply both displayed strong nonlinear transitions, suggesting that shortage was controlled by the combined failure of multiple supply pathways rather than by a single source. Direct river intake showed an apparently counterintuitive pattern, with high intake values associated with positive SHAP contributions. This is consistent with increased intake as an operational response to emerging shortage rather than an independent cause of it. D11 was different again: reservoir supply followed a clear shortage-reducing pattern, whereas wide-area water supply showed positive SHAP contributions at high values. Rather than indicating that increased wide-area supply worsened shortage, this pattern likely reflects compensatory allocation in which wide-area supply was elevated in response to shortage conditions, creating a statistical co-occurrence that the model captured.

The dependence plots therefore sharpen the interpretation of the SHAP heatmap. The important issue is not merely which variable is dominant, but how that variable behaves near operational thresholds. D02 and D03 represent direct supply-limitation systems, D04 reflects multi-source vulnerability, and D11 points to reservoir-sensitive shortage behavior with compensatory wide-area supply. These patterns indicate that domestic water shortage reflects nonlinear and storage-mediated system responses rather than a simple linear function of supply availability [32]. However, the cases of direct river intake in D04 and wide-area water supply in D11 also illustrate that some supply-related variables are not purely exogenous but partly endogenous to the shortage process, so that SHAP values may reflect the direction of statistical association rather than the direction of causation [33,34].

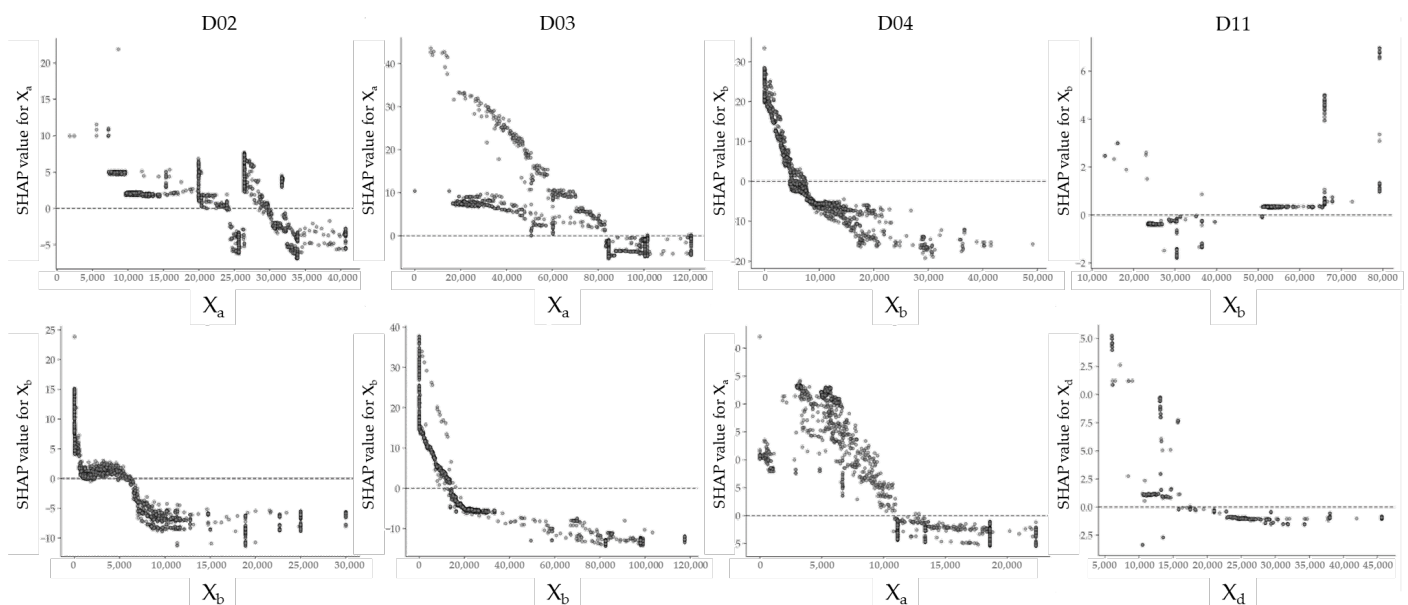


Figure 5. SHAP dependence plots for the dominant explanatory variables.

3.4. Shortage-Event Clustering

Event-based classification was applied to distinguish shortage events with different temporal and severity characteristics, following the broader concept that hydrological drought events can be differentiated according to their underlying characteristics and development process [35]. As summarized in Table 6, the four clusters represented distinct shortage-event types, ranging from severe cumulative events to low-intensity events with different timing characteristics. C2 captured the most severe and persistent shortage type, whereas C4 represented short low-intensity events. C1 and C3 occupied intermediate or timing-specific categories, with C3 mainly distinguished by later peak occurrence.

Table 6. Characteristics and dominant explanatory factors of shortage-event clusters.

Cluster	Characteristics	Mean Duration (pentad)	Mean Shortage Rate (%)	Peak Month	Number of Events	Dominant SHAP Factors
C1	Moderate	5.88	20.93	5	423	X_b (87%), X_d (11%)
C2	Long/Severe	12.83	37.90	4	101	X_b (79%), X_d (20%)
C3	Late/Low-intensity	2.82	9.51	10	361	X_b (65%), X_d (22%)
C4	Short/Low-intensity	2.22	8.08	4	572	X_b (74%), X_a (14%)

The district-level occurrence probabilities revealed clear spatial differences in shortage-event composition (Figure 6b). D02 and D03 showed a predominance of C4, indicating recurrent short and low-intensity shortage events. D04 showed a more balanced mixture of C1 and C4 and the largest share of C2, suggesting exposure to a wider spectrum of shortage conditions, including occasional severe cumulative events. D11 exhibited a relatively high proportion of C3, indicating a distinct late-season low-intensity shortage pattern.

The cluster-level SHAP results further linked these event types to their explanatory factors (Figure 6a). Wide-area water supply was the dominant factor across all clusters, while reservoir supply became more relevant in C2 and C3. This implies that wide-area supply dependence structures most shortage events, but reservoir-related conditions become more important when shortages are cumulative or seasonally delayed.

This event-based classification adds a management-relevant layer to the SHAP analysis and suggests differentiated adaptation priorities. For districts where shortage is primarily associated with wide-area supply reduction, such as D02 and D03, strengthening the resilience of wide-area transmission networks and diversifying local supply sources including emergency interconnections with neighboring systems could help reduce the frequency of recurrent low-intensity shortage events. For districts exhibiting multi-source vulnerability, such as D04, coordinated monitoring across multiple supply pathways and the establishment of operational trigger levels for each supply component may be more effective than reinforcing any single source. For districts where shortage is more closely linked to reservoir conditions with late-season timing, such as D11, adjusted reservoir operational rules, pre-season storage targets, and seasonal demand management could mitigate the risk of late-season supply shortfalls. These district-specific strategies illustrate how the diagnostic results of the XGBoost-SHAP framework can be translated into actionable guidance for water supply planning, moving beyond uniform basin-wide measures toward targeted, source-aware adaptation. Thus, domestic water shortage in the Seomjin River water system differs not only in magnitude and frequency, but also in event structure, timing, and dominant explanatory factors.

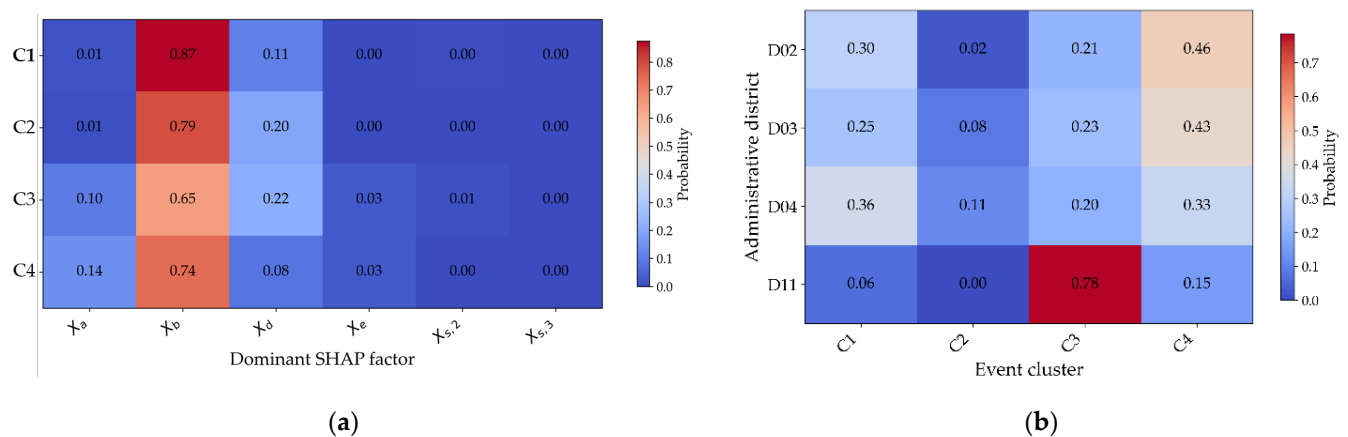


Figure 6. Shortage-event clustering results: (a) dominant SHAP factors by cluster and (b) district-level probability of shortage-event clusters.

4. Conclusions

This study proposed an integrated XGBoost–SHAP diagnostic framework, combined with K-WEAP water supply–demand simulation, to identify the explanatory factors of domestic water shortage under representative drought scenarios in the Seomjin River water system. The framework linked pentadic shortage simulation, machine learning prediction, explainable AI interpretation, and shortage-event clustering to move beyond conventional shortage quantification toward factor-level diagnosis.

The results revealed clear spatial heterogeneity in both shortage occurrence and its underlying explanatory structure. Among eleven administrative districts, only a subset experienced shortage with sufficient frequency for diagnostic modeling, while most districts showed no or negligible shortage under the same drought forcing. This contrast confirms that drought-induced water shortage is not a uniform basin-wide response but is strongly shaped by local source composition, wide-area transfer dependence, and reservoir connectivity. The district-specific XGBoost models reproduced the simulated shortage rates with test R^2 values exceeding 0.91, and SHAP analysis identified two distinct explanatory patterns: shortage primarily associated with wide-area supply in inland districts and shortage more closely linked to reservoir supply in a coastal district. The dependence analysis further revealed threshold-type behavior, in which shortage risk increased sharply once key supply variables fell below district-specific critical ranges. Shortage-event clustering added a temporal dimension, distinguishing recurrent low-intensity events, mixed-severity events, and late-season reservoir-related events across districts.

Several limitations should be acknowledged. First, the diagnostic analysis was restricted to districts with sufficient shortage frequency, excluding the majority of administrative units from explanatory modeling. Second, the use of three representative drought scenarios, while effective for focusing on severe dry conditions, limits the coverage of climate uncertainty. Third, some supply-related variables used as model inputs are not purely exogenous but partly reflect operational responses to shortage conditions, which can cause SHAP values to capture the direction of statistical association rather than causal effects.

The proposed framework provides an interpretable basis for identifying vulnerable districts and diagnosing the mechanisms behind domestic water shortage. Future research should expand the range of climate and demand scenarios, incorporate adaptation measures such as supply diversification and reservoir operation adjustment, and explore causal inference methods to complement the associational interpretation provided by SHAP analysis.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/w18151894/s1>, Figure S1: Calibration results of the K-WEAP model at multiple streamflow gauging stations.; Figure S2: Dryness score calculation procedure, ranking of CMIP6 climate projections, and selection of representative drought scenarios based on ETCCDI precipitation indices. Figure S3: Time series of XGBoost-predicted shortage rates and K-WEAP-simulated shortage events for each district and drought scenario: (a) D02, (b) D03, (c) D04, and (d) D11. Table S1: Variance Inflation Factor values for the explanatory variables used in each district-specific XGboost model.

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