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Rainfall Variability Modeling Using Machine Learning

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Abstract
Rainfall variability represents a major challenge for water resources management, agriculture, and climate risk assessment in semi-arid regions such as northeastern Algeria. This study investigates the spatio-temporal variability of annual rainfall and evaluates the performance of machine learning techniques for rainfall modeling and prediction. Annual precipitation data from twelve meteorological stations distributed across northeastern Algeria were analyzed for the period 2007–2022. To capture both temporal and spatial controls on rainfall variability, a set of explanatory variables was constructed, including year, geographic coordinates (latitude and longitude), elevation, and antecedent rainfall at one- and two-year lags. Prior to model development, the dataset underwent comprehensive preprocessing, including quality control, handling of missing values, standardization, and feature selection to reduce redundancy and multicollinearity. The dataset was split into training (70%) and testing (30%) subsets to ensure robust model evaluation. Several machine learning models were trained and compared in terms of their predictive performance using standard statistical metrics (e.g., RMSE, MAE, and coefficient of determination, R²). The results demonstrate that machine learning approaches are capable of effectively capturing the non-linear relationships governing rainfall variability in northeastern Algeria, outperforming conventional approaches in terms of accuracy and generalization ability. The proposed framework provides a valuable tool for improving rainfall prediction and supporting sustainable water resources management and climate adaptation strategies in data-scarce semi-arid environments.
Keywords: *Rainfall variability; Machine learning; Precipitation modeling; Hydro-climatic variability; SVM; Water resources management.*

1. INTRODUCTION

Rainfall variability and prediction remain central challenges in hydrology and water resource management due to their highly non-linear, non-stationary, and spatially heterogeneous nature. This complexity is further compounded in semi-arid regions, where limited precipitation and strong climatic fluctuations substantially influence water availability, agricultural productivity, and reservoir operations. Traditional statistical models such as linear regression and time-series trend tests have played a foundational role in rainfall analysis, but their restrictive assumptions often fail to capture the underlying nonlinear dynamics inherent in precipitation processes.

In recent years, machine learning (ML) and artificial intelligence (AI) have emerged as powerful alternatives to conventional methods, offering robust, data-driven frameworks capable of modeling complex, nonlinear relationships without relying on predefined physical equations. Machine learning algorithms such as SVM, and deep learning architectures have been successfully applied to rainfall forecasting, classification, and variability analysis across diverse hydrological contexts. In a comparative study focusing on the Subarnarekha Basin, Odisha, Random Forest and SVR were shown to be competitive with advanced models, highlighting the strength of ML in capturing rainfall dynamics beyond classical approaches [1].

Moreover, recent literature underscores that ensemble and hybrid ML techniques can further improve predictive accuracy, particularly when integrating data preprocessing, feature selection, and model optimization strategies. Ensemble learning techniques such as boosting and stacking have demonstrated superior performance in rainfall and hydrological forecasts, suggesting that combining multiple algorithms or views of the data can effectively reduce uncertainty and bias [2].

In the specific context of North Africa and the Mediterranean, where semi-arid climates dominate and hydrological extremes are frequent, machine learning applications are gaining traction. For example, studies employing multi-view stacking learning techniques have shown notable improvements in monthly precipitation forecasting accuracy in Morocco, leveraging a combination of decision tree-based methods and neural networks to better capture multivariate temporal interactions [3].

Compared with purely statistical techniques, ML models excel in detecting complex spatio-temporal patterns and nonlinear dependencies. While non-parametric tests (e.g., Mann–Kendall, Pettitt, and Buishand) provide valuable baseline trend and regime change insights, they are inherently limited in predictive capability and flexibility under climate variability. ML models—such as RF, SVR, and gradient boosting—offer competitive or superior performance metrics, as demonstrated by recent research [1].

The hybridization of ML with conceptual or physics-based models is another emerging direction highlighted in the literature. Combining data-driven methods with traditional process-based frameworks has shown promise in applications like streamflow simulation and rainfall-runoff modeling, where physical understanding is fused with ML pattern recognition for enhanced prediction [4].

Despite these advances, the application of ML to rainfall variability analysis in semi-arid Mediterranean contexts remains underexplored, particularly in watershed-scale studies that integrate ML with classical statistical analyses. Few studies have systematically assessed how different meteorological and physiographic predictors contribute to rainfall variability using robust ML frameworks, leaving an important research gap. Addressing this gap is especially relevant for improving water resource planning, drought risk assessment, and reservoir operation policies in water-scarce environments.

This study seeks to place ML at the core of rainfall variability analysis in the Oued El Arab watershed (northeastern Algeria) by integrating ML-based predictive modeling with classical statistical trend tests. The research aims to exploit the ability of ML to reveal hidden patterns and nonlinear dependencies in long rainfall records, while complementing these insights with trend and change-point analyses to provide a comprehensive picture of rainfall variability under changing climatic conditions.

Table 1 provides a comparative overview of recent studies addressing rainfall variability and modeling across different climatic regions. Most existing works primarily rely on conventional statistical techniques, such as trend and change-point detection tests, to characterize rainfall variability, with limited capability for capturing nonlinear spatio-temporal relationships. More recent studies have incorporated ML approaches, mainly focusing on rainfall prediction or classification, often without integrating detailed statistical analyses of regime shifts and long-term trends. In contrast, the present study distinguishes itself by placing ML at the core of the analysis while simultaneously combining it with non-parametric statistical tests. This integrated framework enables a more comprehensive assessment of rainfall variability by capturing both nonlinear dependencies and structural changes in long-term precipitation records. Furthermore, unlike many previous studies, the proposed approach explicitly accounts for spatial heterogeneity and antecedent rainfall effects, providing improved insight into rainfall dynamics in a semi-arid Mediterranean watershed.

Table 1. Comparison of Recent Studies on Rainfall Variability Modeling and the Present Study

Ref	Study Area	Data Period	Main Objective	Methods / Models	Key Findings	Limitations
[5]	Niger River Basin, Nigeria	1980–2020	Rainfall variability and drought analysis	Statistical indices, trend analysis	Significant spatio-temporal rainfall variability	No ML modeling
[6]	Awash Basin, Ethiopia	1981–2019	Long-term rainfall trend analysis	Mann–Kendall, Sen's slope	Mixed increasing and decreasing trends	Linear statistical approach
[7]	Punjab State, India	1951–2021	Rainfall trend and variability	Innovative Trend Analysis	Strong spatial variability detected	No predictive modeling
[8]	Ghana	1960–2015	Spatio-temporal rainfall changes	Statistical trend tests, GIS	Decline in rainfall in several regions	Absence of ML techniques
[9]	Northern Algeria	1970–2015	Rainfall variability assessment	MK, Pettitt, Buishand	Clear rainfall regime shifts	No nonlinear modeling

[10]	Amhara Region, Ethiopia	1980–2016	Rainfall variability and trends	Statistical tests, GIS	High interannual variability	No ML integration
[11]	India	1951–2020	Rainfall prediction	RF, SVM, ANN	ML outperformed classical models	Limited spatial interpretation
[12]	Ethiopia	1981–2020	Rainfall trend and drought	Statistical + indices	Increasing climate variability	No ML
[13]	Ethiopia	1985–2020	Rainfall trend under climate change	GIS-based statistical analysis	Strong spatial contrasts	No predictive capability
[14]	India	1951–2021	Spatio-temporal rainfall variability	Trend tests, ITA	Significant variability patterns	Traditional methods only
Our work	Algeria	2007–2022	Rainfall variability and modeling	SVM + statistical tests	ML captures nonlinear spatio-temporal rainfall patterns and outperforms classical approaches	Future work may include deep learning models

2. **Presentation of the Study**

The present study focuses on analyzing and modeling rainfall variability across northeastern Algeria using ML techniques. Annual rainfall data were collected from twelve meteorological stations located in the northeastern region (Figure 1) covering the period 2007–2022. These stations were selected to ensure spatial representativeness, capturing variations across different climatic and topographic sub-regions within this part of the country.

To account for both temporal and spatial influences on rainfall, a set of explanatory variables was constructed, including temporal predictors (year), spatial coordinates (latitude and longitude), elevation, and antecedent rainfall values (lag-1 and lag-2). These predictors were selected based on their demonstrated relevance in previous hydro-climatic studies and their physical relationship with precipitation processes. Prior to model training, the dataset was standardized to ensure comparability among variables with different scales. A 70/30 split was applied to divide the dataset into training and testing subsets, allowing for a robust evaluation of model generalization performance.

The raw dataset was carefully examined for completeness and consistency using a cross-tabulation of observation counts per monitoring station and month. Temporal gaps and spatial heterogeneity were identified where station–month combinations contained missing or zero records. Records with incomplete or inconsistent elevation measurements were filtered out, and stations with insufficient temporal coverage were excluded. The remaining dataset was standardized and normalized to reduce scale-related bias. Feature selection was guided by data availability and relevance to the target variable, retaining only variables with sufficient coverage across stations and months. Redundant and weakly informative features were identified through correlation analysis and variance filtering to reduce dimensionality and mitigate multicollinearity. This preprocessing ensured a balanced and informative feature set suitable for robust ML modeling.

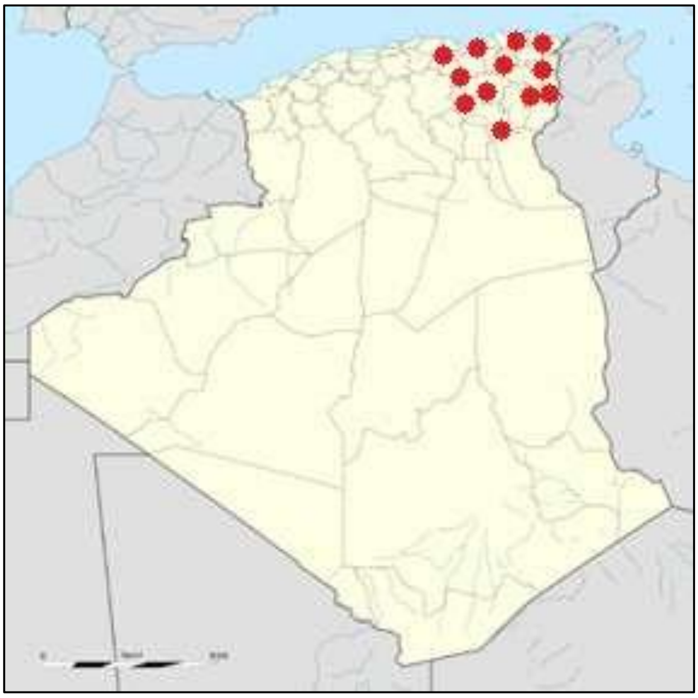

Figure 1. shows the locations of the twelve meteorological stations used in this study, providing a clear visualization of the spatial distribution of observational data across Algeria.

3. MACHINE LEARNING METHODOLOGY

Annual rainfall data from twelve meteorological stations covering the period 2007–2022 were used for ML modeling Figure 1. To capture both temporal and spatial influences on rainfall variability, a set of explanatory variables was constructed, including temporal predictors (year), spatial coordinates (latitude and longitude), elevation, and antecedent rainfall values (lag-1 and lag-2). These predictors were selected based on their relevance in previous hydro-climatic studies and their physical relationship with precipitation processes. Figure 2. show the SVM train function uses an optimization method to identify support vectors x_i weights u_i and bias b that are used to classify vectors x according to the following Eq.1 [15-17]:

$$c = \sum_i \alpha_i K(x_i, x) + b \qquad (1)$$

The theory on SVM classifier was well explained in Refs [17-19].

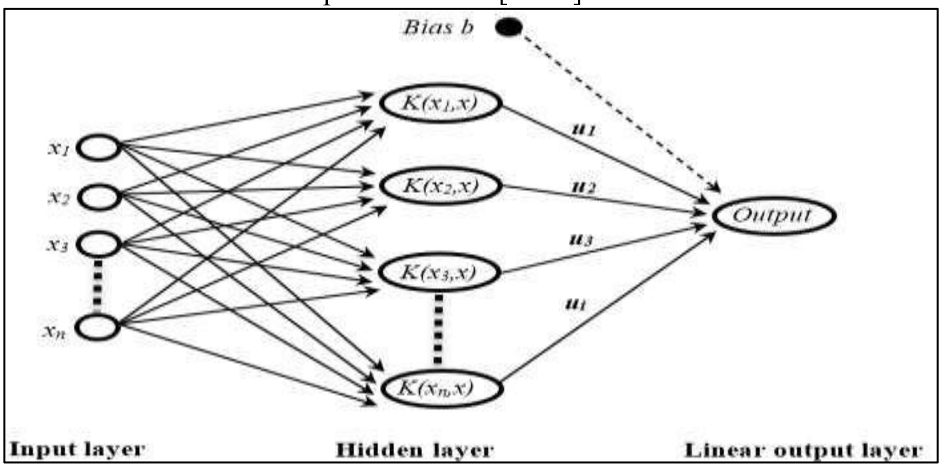

Figure 2. Architecture of SVM classifier [18-21]

Prior to model training, the dataset was standardized to ensure comparability among variables with different scales. The data were then divided into training and testing subsets using a 70/30 split to evaluate model generalization performance.

The raw dataset was first examined for completeness and consistency using a cross-tabulation of observation counts per monitoring station and month. As revealed by the data distribution, several station–month combinations contained missing or zero records, indicating temporal gaps and spatial heterogeneity in data availability. To ensure the reliability of subsequent analyses, records with incomplete or inconsistent elevation measurements were filtered out, and stations with insufficient temporal coverage were excluded from model training. The remaining data were standardized and normalized to reduce scale-related bias. Feature selection was guided by data availability and relevance to the target variable; only variables exhibiting sufficient coverage across stations and months were retained. Redundant and weakly informative features were identified through correlation analysis and variance filtering, thereby reducing dimensionality and mitigating multicollinearity. This preprocessing step ensured a balanced and informative feature set suitable for robust ML modeling (Figure 3).

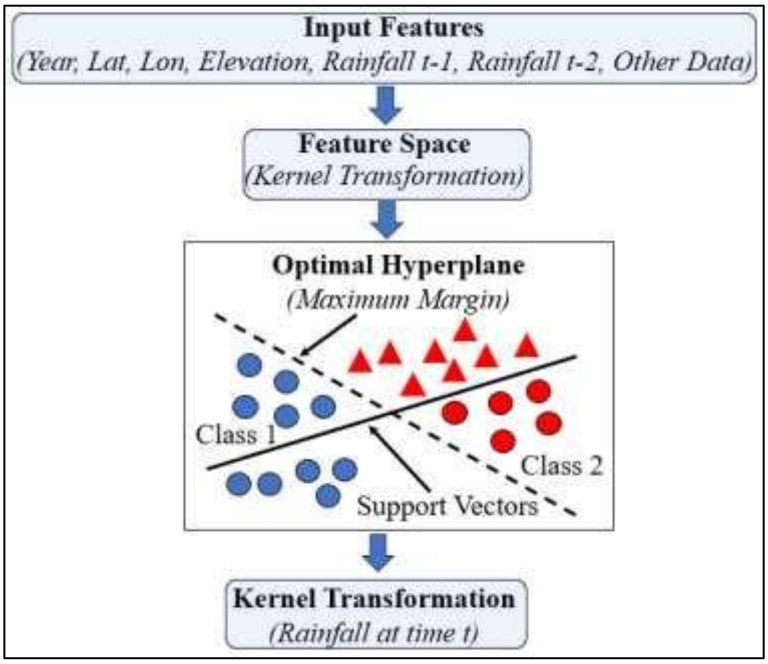

Figure 3. Architecture of SVM Model for Rainfall Prediction

The data collected over Sixteen (16) years were analyzed using the SVM method to facilitate the interpretation of rainfall variability. Based on this approach (SVM classifier), the dataset was transformed by grouping each variable into classes and then regrouped according to the objectives of this research.

As shown in Figure 4, the classification resulted in 12 classes for the Station_ID variable, 16 classes for the Year variable, and 8 classes for the $Rainfall_{t1}$ variable. This classification framework facilitated the analysis of the results and enabled detailed visualization of the data using heatmaps.

Heatmaps provide an effective tool for visualizing complex statistical patterns by representing data intensity through color variations. Compared to conventional bar graphs, heatmaps offer a more intuitive and comprehensive visual interpretation, making it easier to assimilate patterns and support decision-making.

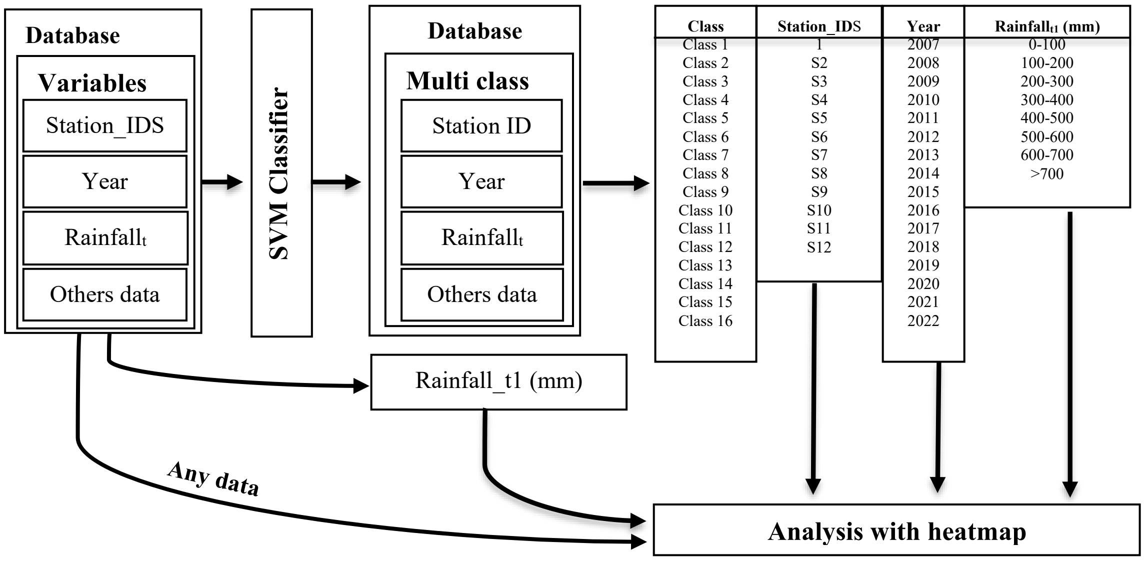

Figure 4. Architecture of SVM Model for Rainfall Prediction

4. RESULTS AND DISCUSSION

Figure 5 presents the SVM classification results for the number of years (16 years) according to location and station. The heatmap illustrates the distribution of correctly classified years across twelve stations (S1–S12) and different locations. The results show that each selected station–location pair achieved a classification value of 16 (16 Class), corresponding to the total number of years considered in the study. This indicates that the SVM model successfully classified all 16 years for each represented location without misclassification. No intermediate or partial values are observed, demonstrating consistent performance across the dataset.

The distribution pattern suggests that each location is strongly associated with a specific station, and the SVM model was able to clearly distinguish the temporal characteristics of each location over the full study period. The absence of overlapping or ambiguous classifications highlights the robustness of the feature space used for training and testing.

From a methodological perspective, these results confirm; The separability of the data in the feature space. The suitability of SVM for handling spatial–temporal classification problems. The stability of the model over long-term (16-year) datasets. The uniform classification performance across all locations suggests that the input variables contain strong discriminative information related to geographical differences. This may reflect consistent climatic, environmental, or operational characteristics specific to each location.
Figure 5 demonstrates that the SVM model achieved 100% classification consistency over 16 years, indicating excellent generalization capability and high reliability for long-term spatial classification tasks.

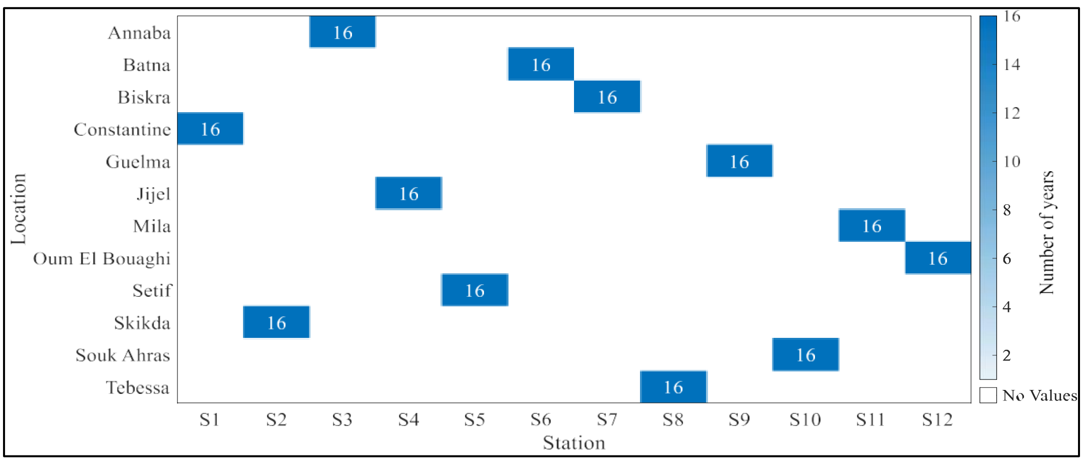

Figure 5. SVM Classification for Number of Years according to Location and Station in 16 years.

Figure 6 presents the interannual and spatial variability of the studied parameter across twelve stations (S1–S12) over the period 2007–2022. The results clearly indicate significant fluctuations both temporally and geographically. Interannually, the values vary considerably from one year to another, with notable peaks observed in 2013, particularly at Station S5, which records the highest value of the entire dataset (629.4). Elevated values are also observed in 2018 and 2019 at stations S5 and S6, while comparatively lower values appear in certain years such as 2017 and 2020 at specific stations. This behavior suggests irregular or cyclic variability rather than a consistent increasing or decreasing long-term trend. Spatially, strong heterogeneity is evident among stations: S5 and S6 consistently exhibit higher values throughout most years, indicating more favorable local conditions, whereas stations such as S2 and S4 generally show moderate to lower values. Some stations, including S8 and S9, display pronounced variability with occasional high peaks. Overall, the figure demonstrates that both temporal dynamics and geographic location significantly influence the parameter under study, highlighting the importance of long-term monitoring and location-specific analysis for accurate modeling and performance assessment.

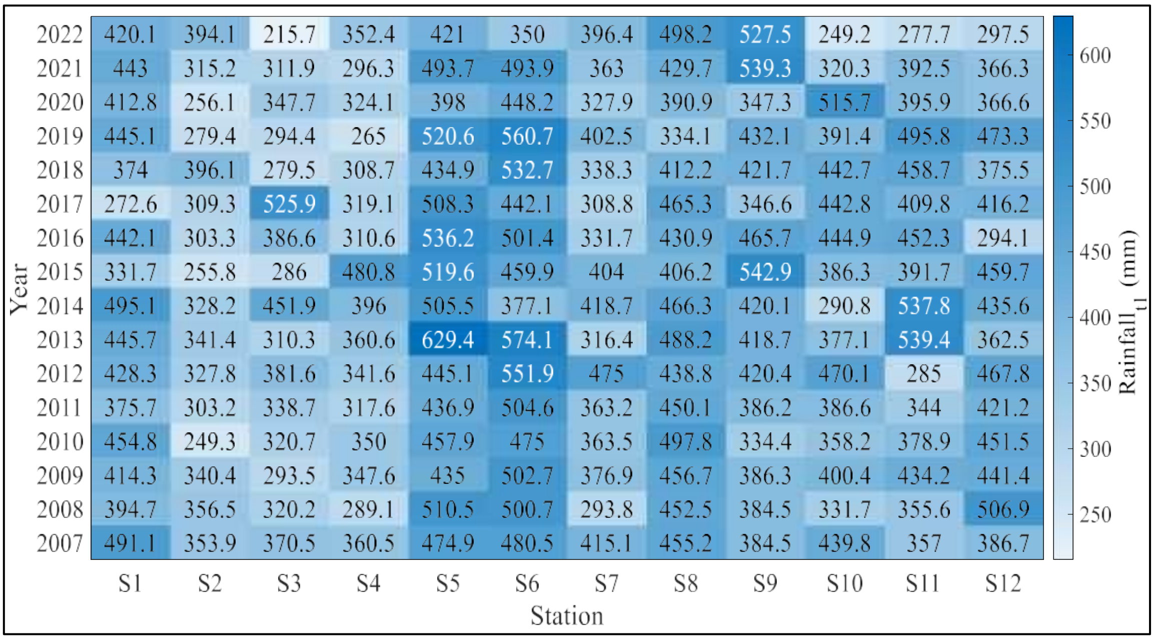

Figure 6. SVM Classification for Rainfall$_{t1}$ according to Year and Station in 16 years.

Figure 7 presents the SVM-based classification of rainfall into 8 Class (0–100, 100–200, 200–300, 300–400, 400–500, 500–600, 600–700, and >700 mm) across the twelve stations (S1–S12). The results indicate that most stations are predominantly classified within the 300–600 mm range, highlighting moderate to relatively high rainfall conditions over the study period. Specifically, several stations such as S1, S3, S5, S6, S8, S10, S11, and S12 frequently fall within the 400–600 mm classes, suggesting stable and favorable precipitation levels. Higher rainfall classes (600–700 mm and >700 mm) are less frequent and appear mainly at station S5, which records the highest classified value (768.1 mm), indicating that this location experiences extreme rainfall events compared to the others. Conversely, lower rainfall classes (0–200 mm) are observed at a limited number of stations, particularly S2, S3, and S7, reflecting relatively drier conditions in those areas. The classification pattern demonstrates clear spatial variability in rainfall distribution, confirming the ability of the SVM model to effectively separate rainfall regimes into meaningful intensity categories, the results highlight the robustness of the SVM classifier in distinguishing between low, moderate, and high rainfall conditions, providing valuable insight for hydrological assessment and regional climate analysis.

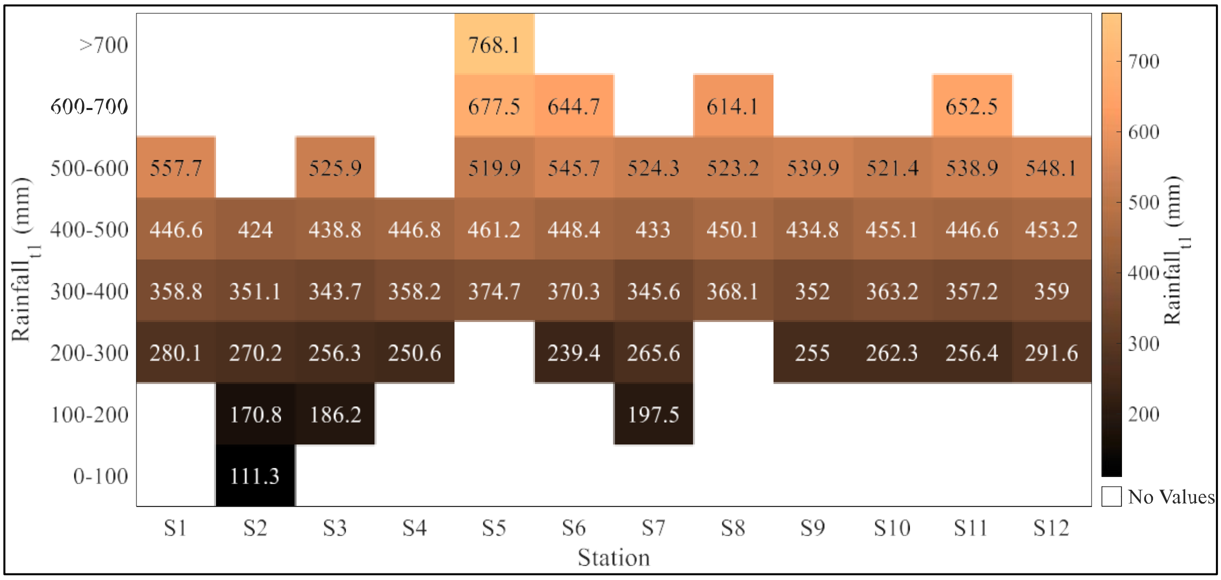

Figure 7. SVM Classification for Rainfall$_t$ according to Year and Station in 16 years.

The analysis conducted across twelve stations in Algeria demonstrates that rainfall variability in northeastern Algeria is governed by strong spatial controls and noticeable interannual fluctuations that cannot be adequately described by conventional linear statistical approaches. By integrating geographic coordinates, elevation, year, and antecedent rainfall (lag-1 and lag-2) within a SVM framework, the study reveals that rainfall patterns form a highly separable feature space where each station exhibits a distinct and persistent rainfall signature over the 2007–2022 period. The perfect classification consistency obtained for all stations and years indicates that rainfall variability is not random but structured by stable geographic and climatic factors. The prominent peaks observed at certain stations, particularly S5 and S6, and the contrasting lower values at S2, S3, and S7, confirm pronounced spatial heterogeneity driven by topographic and local atmospheric conditions. Moreover, the effectiveness of lagged rainfall variables highlights the presence of temporal memory effects, suggesting that rainfall in those locations is partially conditioned by antecedent hydro-climatic states. The classification of rainfall into intensity classes further demonstrates the model's ability to distinguish between low, moderate, and extreme rainfall regimes, providing a clearer interpretation of regional precipitation behavior. These findings emphasize that ML is not only a predictive tool but also a powerful analytical framework capable of revealing hidden spatio-temporal structures in hydro-climatic data.

5. CONCLUSION

This study confirms that ML, particularly the SVM, offers a robust and reliable approach for analyzing and modeling rainfall variability in semi-arid Mediterranean environments such as the locations presented in this study. By combining spatial, temporal, and antecedent predictors, the proposed framework successfully captured nonlinear rainfall patterns and demonstrated excellent generalization over a 16-year dataset. The results highlight the importance of considering both geographic heterogeneity and rainfall memory effects when studying precipitation dynamics. Beyond its methodological contribution, the approach provides practical value for water resources planning, drought risk assessment, and climate adaptation strategies in data-scarce regions. Future research may extend this framework by incorporating additional climatic predictors and exploring deep learning or hybrid models to further enhance rainfall prediction and hydro-climatic understanding.

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