Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 19 No. 16 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijim.v19i16.54923

PAPER

Advanced Model for Predicting Weather Conditions for Smart Grape Cultivation: A Comparative Study between Kosovo and Iowa

Zirije Hasani[1], **Joshua Peschel**[2], **Curtis Youngs**[3], **Jakup Fondaj**[4] (✉), **Randall Vos**[5]

[1]Faculty of Computer Science, University "Ukshin Hoti", Prizren, Kosovo

[2]Department of Agricultural and Biosystems Engineering, Iowa State University, Ames, Iowa

[3]Department of Animal Science, Iowa State University, Ames, Iowa

[4]Faculty of Contemporary Science and Technology, South East European University, Tetovo, North Macedonia

[5]Department of Horticulture, Iowa State University, Ames, Iowa

jf13459@seeu.edu.mk

ABSTRACT

Smart agriculture, powered by data and advanced technologies, is transforming traditional farming practices. Given the sensitivity of grapevine cultivation to climate variability, accurate weather prediction is essential for optimizing yield and quality. This study introduces a predictive model designed to enhance smart grape cultivation through a comparative analysis between Kosovo and Iowa. The model forecasts weather conditions and determines optimal timing for grape spraying, using historical weather data and advanced forecasting techniques. Four algorithms—NeuralProphet, SARIMA (Seasonal AutoRegressive Integrated Moving Average), Random Forest Regression, and a Keras-based Artificial Neural Network (ANN)—are evaluated. The accuracy and performance of the model are evaluated using metrics like mean absolute error (MAE), root mean square error (RMSE), and mean squared error (MSE). By providing timely, data-driven insights for protective treatments, the study aims to improve cultivation efficiency, maximize yield quality, and minimize losses. The comparative approach also highlights regional climatic differences, offering tailored strategies for effective grape management.

KEYWORDS

smart agriculture, machine learning, grapevine cultivation, weather data prediction, grape spraying

1 INTRODUCTION

Grape cultivation is highly sensitive to climatic conditions—particularly temperature, humidity, and precipitation—which directly influence vine growth, disease incidence, and fruit ripening. Given the global importance of grape production for winemaking and consumption, the development of accurate weather prediction models is crucial. This study aims to design an advanced, region-specific model tailored to the needs of grape growers in Kosovo and Iowa, two regions characterized

Hasani, Z., Peschel, J., Youngs, C., Fondaj, J., Vos, R. (2025). Advanced Model for Predicting Weather Conditions for Smart Grape Cultivation: A Comparative Study between Kosovo and Iowa. *International Journal of Interactive Mobile Technologies (iJIM)*, 19(16), pp. 108–132. https://doi.org/10.3991/ijim.v19i16.54923

Article submitted 2025-02-15. Revision uploaded 2025-05-11. Final acceptance 2025-06-18.

© 2025 by the authors of this article. Published under CC-BY.

by distinct climates and soil conditions. By leveraging machine learning techniques and real-time environmental data, the proposed model forecasts weather-related risks and supports more informed, adaptive cultivation practices.

Modern agriculture increasingly relies on smart farming to enhance crop yields, optimize resource use, and improve overall productivity. Predictive modeling and anomaly detection play a central role in this transformation. This study builds on these technologies to advance grape cultivation in alignment with precision agriculture and sustainability goals. Through the integration of advanced data-driven approaches, our objective is to optimize grape yield, quality, and resource efficiency. The methodology combines laboratory experiments, data analysis, and field trials to validate model performance. The focus of this study is on grape cultivation in Kosovo and the United States (specifically Iowa), enabling a comparative analysis of how climatic variations impact grape quality and yield.

As in many other industries, agriculture is increasingly recognizing the strategic value of data. Technologies such as artificial intelligence, data mining, and integrated information systems enable farmers to better understand and respond to the dynamics of their land. These tools not only assist individual producers but also aid government agencies and academic researchers in making informed, data-supported decisions. The accessibility of such insights enhances decision-making across the agricultural sector.

The evolution of human civilization has been closely linked to agricultural development. Agricultural landscapes reflect both the environmental and cultural heritage of the communities that cultivate them. Today's challenges—ranging from food security and natural resource management to environmental sustainability and population growth—demand coordinated responses from governments and institutions. Historically, efforts to support agriculture were limited by factors such as climate variability and volatile markets. However, modern technological advancements now offer more adaptive and sustainable solutions.

"Smart agriculture" refers to the application of digital technologies to replicate, monitor, and optimize agricultural processes [21] [22] [23]. This transformation reduces physical labor and enhances decision-making through precise interventions, efficient resource use, and improved yield management. It also facilitates better economic and administrative control over agricultural production systems.

In response to the growing impacts of climate change, this study investigates grape cultivation practices in Kosovo and Iowa. The study examines how variations in climate affect grape yield and quality, using sensor-based data collected from vineyards in the Prizren region of Kosovo and comparable data from Iowa. Interviews with local farmers further enrich the dataset, providing insight into cultivation techniques, grape processing, and sterilization timing.

Kosovo's continental climate, with its hot, dry summers, offers favorable conditions for grape production but also introduces risks such as frost and abrupt temperature fluctuations. In contrast, Iowa's humid continental climate—characterized by high rainfall and humidity—creates a favorable environment for grape diseases such as downy mildew. These differing climatic challenges highlight the need for a robust, localized model capable of forecasting and mitigating weather-related risks to improve both grape yield and quality.

Kosovo and Iowa were chosen for this study due to their limited representation in existing viticultural research compared to well-studied regions such as Italy, France, and California. By analyzing the unique climate conditions in these areas, we aim to develop models that provide practical support for local grape growers. Given the significant regional differences in climate, predictive models from other viticultural zones cannot be directly applied without adaptation. This study is motivated by the increasing economic pressures caused by climate change and the urgent need for localized, climate-aware agricultural solutions.

The remainder of this paper is structured as follows: Section 2 reviews related work. Section 3 presents the study's objectives and methodology. Section 4 provides weather prediction results and a correlation analysis of climatic variables in Kosovo and Iowa. Section 5 introduces a model for determining optimal grape spraying times. Section 6 discusses the key findings, and Section 7 concludes the study.

2 RELATED WORKS

Weather prediction models have been extensively applied in agriculture, focusing on crops like corn, wheat, and rice. However, few studies have specifically targeted grape cultivation, despite its sensitivity to microclimatic changes. Previous models have relied on basic meteorological data and generalized algorithms that lack region-specific precision. With the advent of big data analytics and machine learning, predictive models can now integrate a wider range of variables, including soil moisture, disease spread, and vineyard microclimates.

Kosovo has seen limited research on weather prediction models for viticulture, despite its growing wine industry. Iowa, while better known for crops like corn and soybeans, has a small but emerging grape-growing sector. Studies show that grapevines can thrive in both regions with proper climate management, but the development of predictive models tailored to local conditions is still in its infancy. Table 1 below presents a comparative overview of weather prediction models in agriculture. We have defined the aspects based on which the comparison is done. Also, we focus on two categories of crop: the first group, corn, wheat, and rice, and the second group, grapes. The table presents a comparison between two countries, Iowa and Kosovo.

Table 1. Comparative overview of weather prediction models in agriculture

Aspect	General Crop Focus (Corn, Wheat, Rice)	Grape Cultivation	Kosovo	Iowa
Research Volume	Extensive	Limited	Minimal research despite wine industry growth	Limited, emerging grape sector
Model Specificity	Generalized models based on basic meteorological data	Requires microclimate sensitivity	No tailored model exists	No tailored model exists
Technological Integration	Basic algorithms, some using ML and big data	Needs integration of vineyard-specific variables	Lacks advanced modeling tools	Lacks advanced modeling tools
Variables Considered	Temperature, precipitation, etc.	Also needs soil moisture, disease presence, microclimate	No integrated datasets available	No integrated datasets available
Regional Modeling Gap	Many region-specific models exist	Few models tailored to specific grape-growing regions	Unaddressed in literature	Unaddressed in literature
Implication	Improved yield predictions for staple crops	Potential to boost grape production and disease control	High potential if models are developed	High potential if models are developed

The authors of this paper [1] present a detailed exploration of automated anomaly detection systems, particularly in the context of smart cities. Their approach synthesizes a variety of methodologies and techniques, addressing the challenges posed by different sensor types and data acquisition protocols commonly found in urban environments.

In the field of anomaly detection, existing literature [2] thoroughly discusses the issues related to sensor data collection and identification of irregularities. These challenges, often linked to the strategic placement of sensors and variability in data quality, are tackled through various proposed solutions. The paper systematically explores these difficulties and outlines strategies to overcome them.

Another notable study [3] contributes to this domain by proposing a comprehensive framework for real-time monitoring of data streams from sensor networks. The study's methodology is highly adaptable, designed to manage diverse data protocols from different sensor access points, specifically within the infrastructure of smart cities.

A specialized system for real-time Internet of Things (IoT) anomaly detection [4] has also been developed. This architecture integrates five unique detection algorithms to accurately pinpoint outliers. A consensus mechanism, supported by a decision function, determines whether a given data point in the time series truly represents an anomaly, ensuring precise identification.

Addressing anomaly classification in multiple IoT environments, another paper [5] introduces two key contributions. The first is a novel methodological framework that promises to fuel future research, while the second focuses on extending anomaly detection techniques for broader application across various IoT contexts.

Innovative techniques continue to advance the field, such as the introduction of the GEER-DLAD system [6], which is designed to optimize IoT-based applications. This technique gathers data from IoT devices, compresses it using the ELC technique, and then employs the MSO algorithm to determine the most efficient routing path for data transmission.

In another study [7], the creation of a labeled IoT dataset for anomaly detection is highlighted. This dataset features a Dynamic Adaptive Detection (DAD) approach coupled with real-world traffic data, providing insights into diverse anomaly scenarios. Machine learning algorithms are applied to analyze data from IoT devices, improving the accuracy of anomaly detection.

Further expanding the scope of research, a study [8] examines anomaly detection in the field of smart agriculture. This study focuses on combining algorithms such as MLR and LSTM to achieve optimal results, emphasizing the importance of detecting anomalies in agricultural applications.

A separate investigation [9] into anomaly detection solutions within the IoT ecosystem highlights common practices, such as the use of hash-based or log-based comparisons. These methods, while effective in many cases, often fail to detect hidden anomalies, underscoring the need for more sophisticated detection strategies.

A novel approach [10] integrates IoT advancements into urban systems for hazard detection, utilizing observational data to preemptively identify weather-related threats. This early detection system plays a crucial role in saving lives and minimizing property damage by recognizing potential hazards before they escalate.

Building on the body of existing research [11], another paper explores the vulnerabilities of IoT devices in decentralized transmission frequency management systems. The study delves into the tactics used by attackers to manipulate transmission frequency and data stream speeds, discussing the various strategies employed to mitigate such risks.

Smart cities are a key focus of IoT research, and one paper [12] outlines an automated system for detecting anomalies within urban IoT networks. The system successfully identifies different types of anomalies across a range of contexts, from mobile devices to vehicles and air sensors, using data gathered from multiple sensors deployed throughout smart city infrastructure.

Given the wide array of anomaly detection algorithms available, a comprehensive review [13] provides a classification of these methods. It highlights three primary categories—testing, semi-testing, and detection of unavailable data—each using specific algorithms, such as support vector machines (SVM) and artificial neural networks (ANN), to detect faults. Semi-supervised error detection methods are also explored, employing Auto-Encoders, Gaussian Models, and Kernel Density Estimation techniques.

The role of fog computing [14] in smart city anomaly detection and secure data transmission is also discussed in detail. This paper emphasizes how fog computing can help meet the rigorous demands of smart city applications by enabling more efficient and secure data management.

In the realm of precision agriculture, deep convolutional neural networks and unmanned aerial vehicles (UAVs) are used for detecting anomalies in grape cultivation [15]. This study showcases the potential of these advanced technologies in enhancing the precision and efficiency of agricultural monitoring systems.

A conference paper [16] delves into the application of IoT and machine learning technologies for anomaly detection in precision agriculture, emphasizing their relevance to smart farming and vineyard management. Similarly, a comprehensive review [17] explores machine learning algorithms' applications in precision agriculture, offering insights into predictive modeling and anomaly detection, particularly within grape cultivation.

A separate study [18] demonstrates the use of deep learning techniques for in-field grapevine detection, highlighting their potential in enhancing smart agricultural practices. This innovation represents a significant step forward in automated detection systems for anomaly management.

Additional research [19] focuses on automated methods for detecting powdery mildew in vineyards, a key challenge in grape cultivation. This paper underscores the importance of early and accurate detection to prevent the spread of this common disease.

A study [20] investigates the use of 3D deep learning and hyper-spectral imaging to identify plant diseases, a crucial aspect of improving anomaly detection capabilities in grape farming.

In the growing field of data-driven agriculture, another study [24] explores the integration of remote sensing technologies to monitor environmental factors like soil moisture and precipitation. This study provides critical insights for the early detection of crop diseases and supports sustainable farming practices.

Another paper [25] discusses the deployment of low-cost IoT sensor platforms in vineyards, enabling real-time monitoring and predictive modeling of environmental conditions. This technology enhances grape production by offering timely recommendations for irrigation and disease management.

Further advancements in this domain include a study [26] utilizing convolutional neural networks (CNNs) for early diagnosis of grape diseases. By integrating real-time environmental data, this approach improves disease prediction and management, aligning with modern precision agriculture trends. This study [46] trajectory emphasizes the vital role of technological innovations in advancing anomaly detection across a range of industries, from urban smart cities to agricultural practices.

This study [47] aims to enhance farmers' productivity and improve crop planning through a hydroponics system that precisely controls key environmental factors essential for plant growth, including temperature, humidity, water temperature, pH, and electrical conductivity. Utilizing the IoT, the system provides real-time monitoring, control, and notifications, enabling farmers to promptly adjust conditions and optimize crop treatment.

In Table 2, a comparison overview of anomaly detection in IoT agriculture is provided.

Table 2. Comparative overview of anomaly detection systems in IoT and agriculture

Reference	Focus Area	Approach/Method	Application Domain
[1]	Smart cities	Automated anomaly detection using diverse methodologies	Urban IoT networks
[2]	Sensor variability issues	Strategies for data acquisition and placement	General IoT systems
[3]	Real-time monitoring	Framework adaptable to diverse sensor protocols	Smart cities
[4]	IoT anomaly detection architecture	Five-algorithm detection with decision consensus	General IoT
[5]	Multi-IoT environments	Framework for classification and extension of detection methods	General IoT
[6]	IoT routing optimization	GEER-DLAD system with ELC compression and MSO algorithm	IoT data transmission
[7]	IoT dataset creation	Dynamic Adaptive Detection (DAD) + real-world data	IoT anomaly scenarios
[8]	Smart agriculture	Combined MLR and LSTM for anomaly detection	Agricultural monitoring
[9]	Traditional detection issues	Limitations of hash/log-based methods	IoT ecosystems
[10]	Urban hazard detection	Early threat identification using observational data	Weather and disaster prediction
[11]	IoT security vulnerabilities	Mitigation strategies in decentralized frequency management	IoT communication networks
[12]	Urban anomaly detection	Systematic urban IoT anomaly detection	Smart cities
[13]	Algorithm classification	SVM, ANN, Auto-Encoders, Gaussian Models, KDE	General anomaly detection
[14]	Fog computing in anomaly detection	Secure and efficient data transmission	Smart cities
[15]	Grape cultivation	Deep CNN + UAVs for monitoring	Precision viticulture
[16]	Smart farming	IoT + ML in vineyard anomaly detection	Precision agriculture
[17]	Algorithm application review	Overview of ML models in anomaly detection	Precision agriculture
[18]	Grapevine detection	Deep learning for in-field detection	Vineyard monitoring
[19]	Disease detection	Automated powdery mildew detection	Viticulture disease control
[20]	Hyper-spectral imaging	3D DL + spectral data for disease detection	Vineyard disease management
[24]	Environmental monitoring	Remote sensing for soil moisture and precipitation	Sustainable agriculture
[25]	Real-time monitoring	Low-cost IoT platforms for prediction	Vineyard management
[26]	Early disease detection	CNN + real-time data for grape disease prediction	Precision grape farming

Despite substantial advances in weather prediction and anomaly detection, no existing studies have focused on grape cultivation in **Kosovo** or **Iowa**, nor do any comparative models exist between these two regions. Current literature primarily targets staple crops or generalized IoT applications, lacking the granularity needed for viticulture. Our study is distinctive in that it develops a weather prediction model tailored to these under-researched regions, integrating local environmental and agricultural factors. This region-specific focus addresses a critical gap and offers practical tools for vineyard management in emerging wine industries.

3 RESEARCH OBJECTIVES AND METHODOLOGY

The primary goals of this project are defined by the following key objectives:

- **Data Acquisition:** Collect data from IoT sensors deployed in the Prizren region of Kosovo, as well as from relevant sources in the United States. This includes data obtained from the Kosovo Hydrometeorological Institute [43], the Vineyard Institute [44], the vineyard at Iowa State University's Horticultural Research Station [42], and private vineyards in Iowa.

- **Data Preparation:** Perform thorough data cleaning and preprocessing to ensure high-quality, consistent datasets that are suitable for subsequent modeling activities.
- **Predictive Modeling:** Evaluate the performance of predictive models designed to estimate grape yield based on various environmental and climatic factors.
- **Cross-Regional Analysis:** Analyze and compare data from both Kosovo and Iowa to understand how regional climatic variations influence grape cultivation, focusing on both yield and quality. Notably, no existing studies propose a model for predicting the optimal time for grape spraying in either of these regions.
- **Recommendations:** Provide actionable recommendations and insights to grape farmers in both regions, helping them to optimize cultivation practices and adapt to changing climate conditions.

Methodology: Our methodology follows a comprehensive, multi-step approach:

- **Data Collection**: Utilize IoT sensors to collect real-time data on key environmental variables such as temperature, soil moisture, wind speed, and atmospheric pressure. In addition, gather historical weather data and conduct interviews with local farmers to enrich and contextualize the dataset.

We have collected weather condition data for both Kosovo [43] and Iowa [42]. Tables 3 and 4 present a sample of the dataset used in this study.

Table 3. Weather data for Ames IOWA

IOWA-Ames Weather Data				
Timestamp	Air Pressure	Humidity	Temperature	Wind Speed
1/1/2018 0:53	1045.8	70.13	–24.39	9.2
1/1/2018 1:53	1045.9	69.99	–25	9.2
1/1/2018 2:53	1046	70.58	–25.61	9.2
1/1/2018 3:53	1046.2	69.73	–26.11	11.5
1/1/2018 4:53	1046.4	69.73	–26.11	12.65
1/1/2018 5:53	1046.4	69.73	–26.11	11.5

Table 4. Weather data for the Kosovo Prizren region

Kosovo-Prizren				
Timestamp	Air Pressure	Humidity	Temperature	Wind Speed
01.01.2018 00:00:00	974.446	100.2	–1.4	0.46
01.01.2018 01:00:00	974.248	100.2	–2.8	0.4
01.01.2018 02:00:00	974.182	100.2	–3	2.52
01.01.2018 03:00:00	973.652	100.2	–3.5	2.22
01.01.2018 04:00:00	973.189	100.2	–2.7	0.89
01.01.2018 05:00:00	972.726	100.2	–4.1	0.7
01.01.2018 06:00:00	972.064	100.2	–2	1.88

The dataset spans from 2018 to 2023 and is used to generate weather predictions for the year 2024. It consists of time-series data with an hourly frequency.

Table 5 presents grape cultivation data from the Kosovo Viticulture Institute for the period 2018 to 2022. Using weather predictions generated by our proposed model, we will analyze this dataset to identify the optimal timing for grape spraying. Additionally, qualitative data was collected through interviews with farmers from both Kosovo and the United States, providing further context and validation for our analysis.

Table 5. Data from the Kosovo Viticulture Institute

		2018	2019	2020	2021	2022
Total number of vineyards						8,473
Total number of farmers						4,960
Area, ha	**Vineyards**	3,272	3,367	3,437	3,471	3,472
	Wine grape	2,455	2,489	2,526	2,533	2,521
	Table grape	816	878	911	938	951
Production, t	**Vineyards**	27,322	19,318	26,330	26,527	23,506
	Wine grape	22,324	14,772	20,049	19,091	16,461
	Table grape	4,998	4,546	6,281	7,435	7,045
Yield, t/ha	**Vineyards**	8.4	5.7	7.7	7.6	6.8
	Table grape	6.1	5.2	6.9	7.9	7.0
	Wine grape	9.1	5.9	7.9	7.5	16.5
Grape price on the market (euro)	**Table grape**	1.09	0.98	1.09	1.20	1.52
Grape price on farm (euro)	**Table grape**	/	0.68	0.63	0.53	0.69
	Wine grape	/	0.21	0.24	0.19	0.23
Wine production, '000 litrers	**Total wine**	11,744	5,754	9,429	7,785	7,862
	White wine	6,234	3,380	5,100	4,744	4,643
	Red wine	5,441	2,325	4,295	3,001	3,140
	Rose wine	69	49	35	40	79
The number of farmers who applied for government grants for grape cultivation		3,012	2,939	2,919	35	2,722

The data for Iowa we get from interviews with farmers, which are presented in Table 6.

Table 6. Data from Iowa private vineyards

Data from SNUS Hill vineyard-IOWA						
	2019	2020	2021	2022	2023	2024
Production, t	28.2	9.62	30.2	20.9	39.8	28.1
Area, ha	2.96	3.16	3.18	3.23	3.16	2.87
Yield, t/ha	9.5	3.0	9.5	6.5	12.6	9.8

A severe windstorm (derecho) occurred in Iowa on August 10, 2020, just a few days before the harvest of the Edelweiss grape variety. Several varieties, including Edelweiss, were either abandoned or experienced yield losses exceeding 50% due to extensive fruit bruising. Later-maturing red varieties, such as Marquette and Frontenac, particularly those planted in north-south row orientations, failed to reach full maturity, likely as a result of both physical bruising and damage caused by the windstorm.

Table 7. Comparison between yield per t/ha for Kosovo and Iowa in the last six years

	2019	2020	2021	2022	2023	2024
Yield, t/ha IOWA	9.5	3.0	9.5	6.5	12.6	9.8
Yield, t/ha Kosovo	5.7	7.7	7.6	6.8	6	18

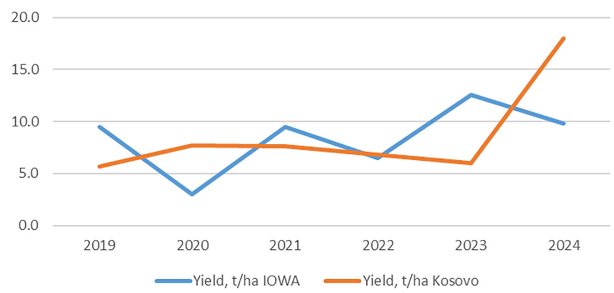

Fig. 1. Comparison of yield per t/ha in Iowa and Kosovo

Figure 1 illustrates that, overall, grape yield per hectare is higher in Iowa compared to Kosovo. This disparity is particularly significant in 2023, a year during which extremely high temperatures in Kosovo caused substantial damage to grape crops. Field visits and interviews with farmers in both regions further revealed that grape spraying practices in Iowa are not only more frequent but also more diverse than those in Kosovo.

Predictive Modeling: To forecast grape yield, we utilize the SARIMA (Seasonal AutoRegressive Integrated Moving Average) model [34], which incorporates historical data, climatic variables, and other relevant factors. The model is designed to be dynamically updated, ensuring sustained accuracy and applicability over time.

In our previous study [33], we conducted a comprehensive evaluation of several predictive algorithms for time-series weather data. These included NeuralProphet [37], Random Forest Regression [38], SARIMA, and Artificial Neural Networks (ANN) implemented using Keras [39]. Following a detailed comparative analysis [33], SARIMA emerged as the most effective model for our specific application.

The SARIMA model outperformed the others based on standard evaluation metrics, including Mean Absolute Error (MAE) [40], Root Mean Square Error (RMSE) [41], and Mean Squared Error (MSE) [41]. The comparative results, as documented in our previous work, are summarized in Table 8.

Table 8. Comparison of predictive algorithms for Kosovo weather data [33]

	NeuralProphet	Random Forest Regression	SARIMA	ANN by KERAS
Mean Squared Error (MSE)	24.0°C^2	38.1°C^2	4.4°C^2	33.6°C^2
Root Mean Squared Error (RMSE)	4.9°C	6.2°C	2.1°C	5.8°C
Mean Absolute Error (MAE)	4.1°C	5.8°C	2.0°C	5.5°C

Based on the results, we conclude that the SARIMA (Seasonal AutoRegressive Integrated Moving Average) model [34] outperforms the other algorithms, as indicated by its lower RMSE [41], MSE [41], and MAE [40] values. These metrics suggest that SARIMA's predictions are more closely aligned with the actual values [33].

This study also evaluated the accuracy of four predictive algorithms using data from Iowa. Among them, SARIMA demonstrated the lowest error rates when compared to NeuralProphet [37], random forest regression [38], and the artificial neural network (ANN) implemented using Keras [39]. The comparative results are summarized in Table 9.

Table 9. Comparison of predictive algorithms for IOWA weather data

	NeuralProphet	Random Forest Regression	SARIMA	ANN by KERAS
Mean Squared Error (MSE)	29.0°C²	43.2°C²	8.4°C²	39.3°C²
Root Mean Squared Error (RMSE)	11.9°C	13.2°C	7.1°C	7.8°C
Mean Absolute Error (MAE)	10.1°C	9.8°C	6.0°C	8.6°C

Also in this study, we will use SARIMA [34] in our proposed model to predict data such as temperature, humidity, wind speed, and air pressure.

4 PREDICTION AND CORRELATION ANALYSES FOR KOSOVO AND IOWA WEATHER DATA

A critical component of our proposed model is the forecasting of weather data. In this section, we present projections for the year 2024, derived from historical data spanning the period 2018 to 2023. The forecast focuses on four key meteorological parameters: temperature, atmospheric pressure, humidity, and wind speed. These predictions are generated for both Kosovo and Iowa, followed by a comparative analysis of the climatic conditions in the two regions.

The Figures 2 and 3 illustrate the 2024 forecasts produced using the SARIMA (Seasonal AutoRegressive Integrated Moving Average) model for each parameter in both regions. Based on these forecasts, several observations can be made:

- **Temperature:** During the summer months, Kosovo experiences higher maximum temperatures compared to Iowa. However, spring temperatures rise earlier in Iowa, with April temperatures exceeding those in Kosovo.
- **Humidity:** Iowa exhibits higher humidity levels during the summer, whereas Kosovo records higher humidity in the winter months.
- **Wind Speed:** Average wind speeds are generally higher in Iowa compared to Kosovo.
- **Atmospheric Pressure:** Iowa also shows higher levels of air pressure relative to Kosovo.

These climatic distinctions highlight the necessity for region-specific agricultural strategies and underscore the importance of localized predictive modeling in viticulture.

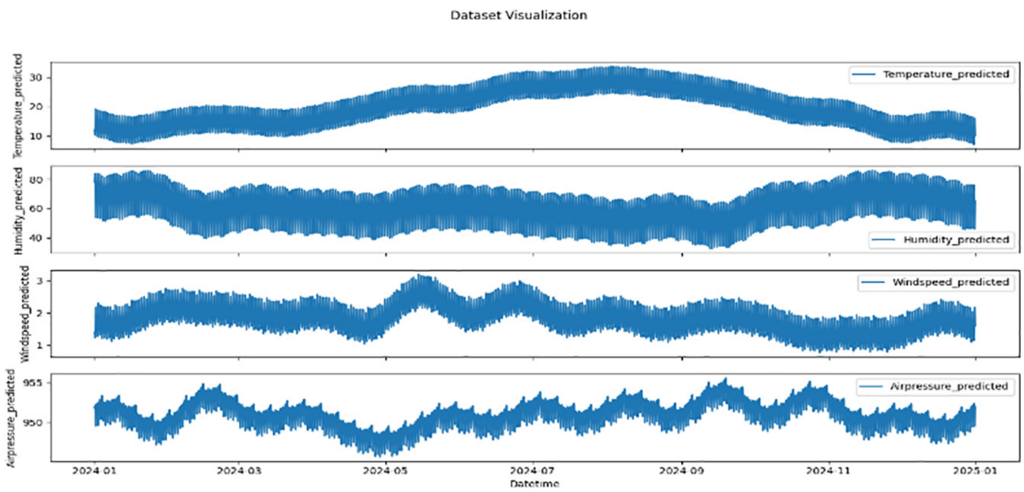

Fig. 2. Prediction of weather data for Kosovo for 2024

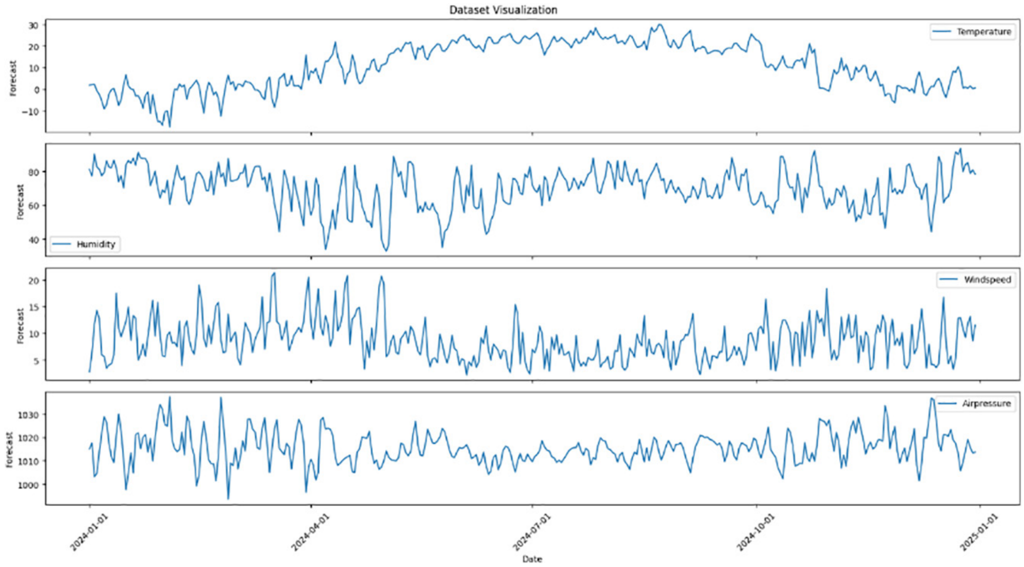

Fig. 3. Prediction of weather data for Iowa for 2024

For each parameter, the original data from 2018 to 2023 is presented alongside the 2024 forecast within a single figure. This approach enables a clear visualization of potential trends, allowing us to assess whether future weather values are expected to increase or decrease compared to previous years.

Figures 4 and 5 present a series of line plots illustrating temperature trends from 2018 to 2023, along with the SARIMA-based forecast for 2024, for both Kosovo and Iowa. These visualizations offer insights into projected temperature patterns and seasonal variations, which are critical for informing agricultural planning and decision-making. A comparative analysis of the two regions reveals the following key observations:

1. **Early Onset of High Temperatures**: In Iowa, higher temperatures begin earlier—typically in April—while in Kosovo, they emerge in May. This difference is significant for viticulture, as it marks the onset of the grape-growing season and is closely tied to the timing of spraying activities. Consequently, grape spraying should commence in early April in Iowa, whereas in Kosovo, it typically begins in early May.
2. **Winter Temperatures**: Winter temperatures in Iowa are lower compared to Kosovo, which experiences relatively milder winters.
3. **Summer Maximum Temperatures**: Kosovo records its highest temperatures in August, which are generally higher than those in Iowa. Elevated temperatures during this period can positively influence grape quality, as higher heat levels contribute to increased sugar content, resulting in sweeter grapes.
4. **Temperature Variability**: Kosovo exhibits greater fluctuations in summer temperatures, suggesting intermittent periods of cooler weather or rainfall. In contrast, Iowa demonstrates more stable summer temperatures, with fewer occurrences of unexpected cold days or rainfall.

These findings emphasize the importance of regional climate patterns in shaping viticultural practices and support the need for localized forecasting tools to optimize grape production.

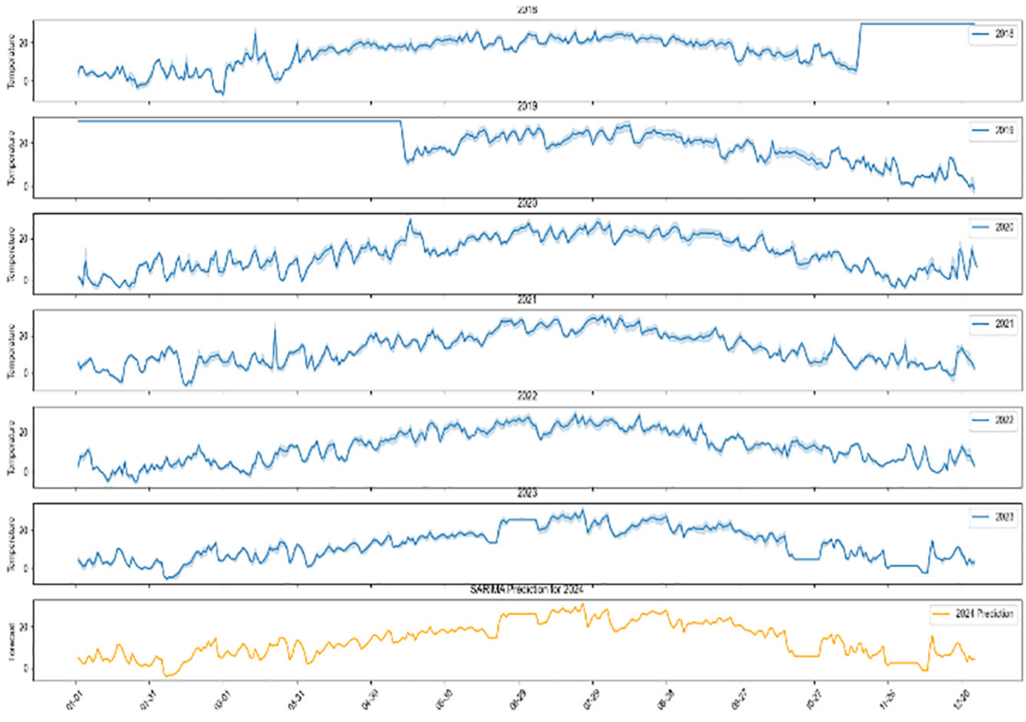

Fig. 4. Result of prediction temperature for 2024 for Kosovo

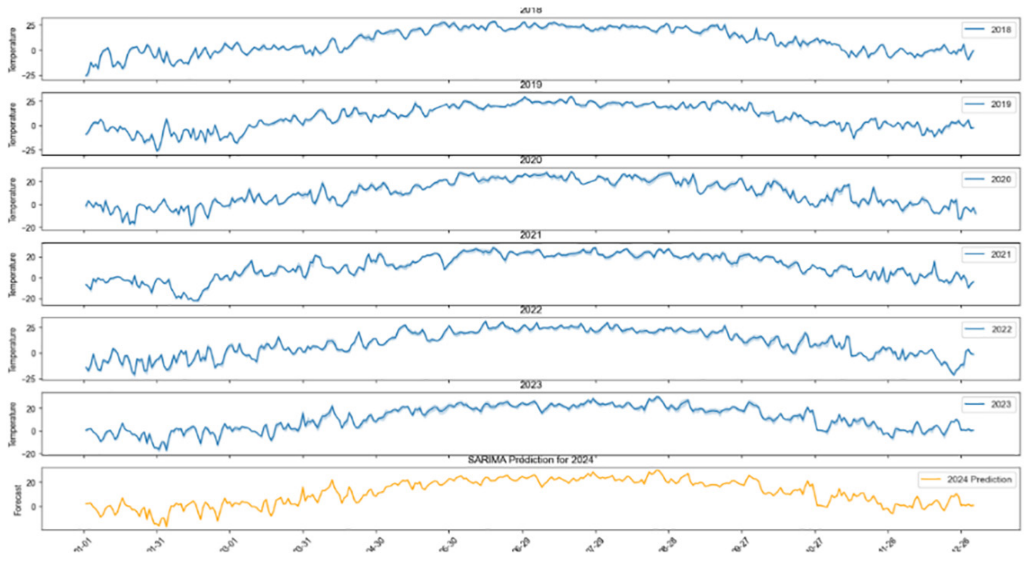

Fig. 5. Result of temperature prediction for 2024 for Iowa

Figures 6 and 7 display a series of line graphs illustrating humidity trends from 2018 to 2023, along with a 2024 forecast generated using the SARIMA model for both Kosovo and Iowa. The projections indicate that humidity levels in 2024 are expected to remain relatively consistent with historical trends observed in previous years. A comparative analysis between the two regions reveals the following key insights:

1. **Grape Cultivation Period (May–September):** During the grape growing season, humidity levels in Kosovo are generally lower than those in Iowa.

Elevated humidity during this period, as observed in Iowa, can increase the risk of grapevine diseases and negatively impact grape quality.

2. **Seasonal Humidity Patterns:** In Kosovo, humidity tends to be higher during the winter months and lower in the summer. Conversely, Iowa experiences higher humidity levels during the summer than Kosovo, which poses additional challenges for disease management in viticulture.

These observations underscore the importance of region-specific humidity monitoring and forecasting to inform disease prevention strategies and optimize grape production outcomes.

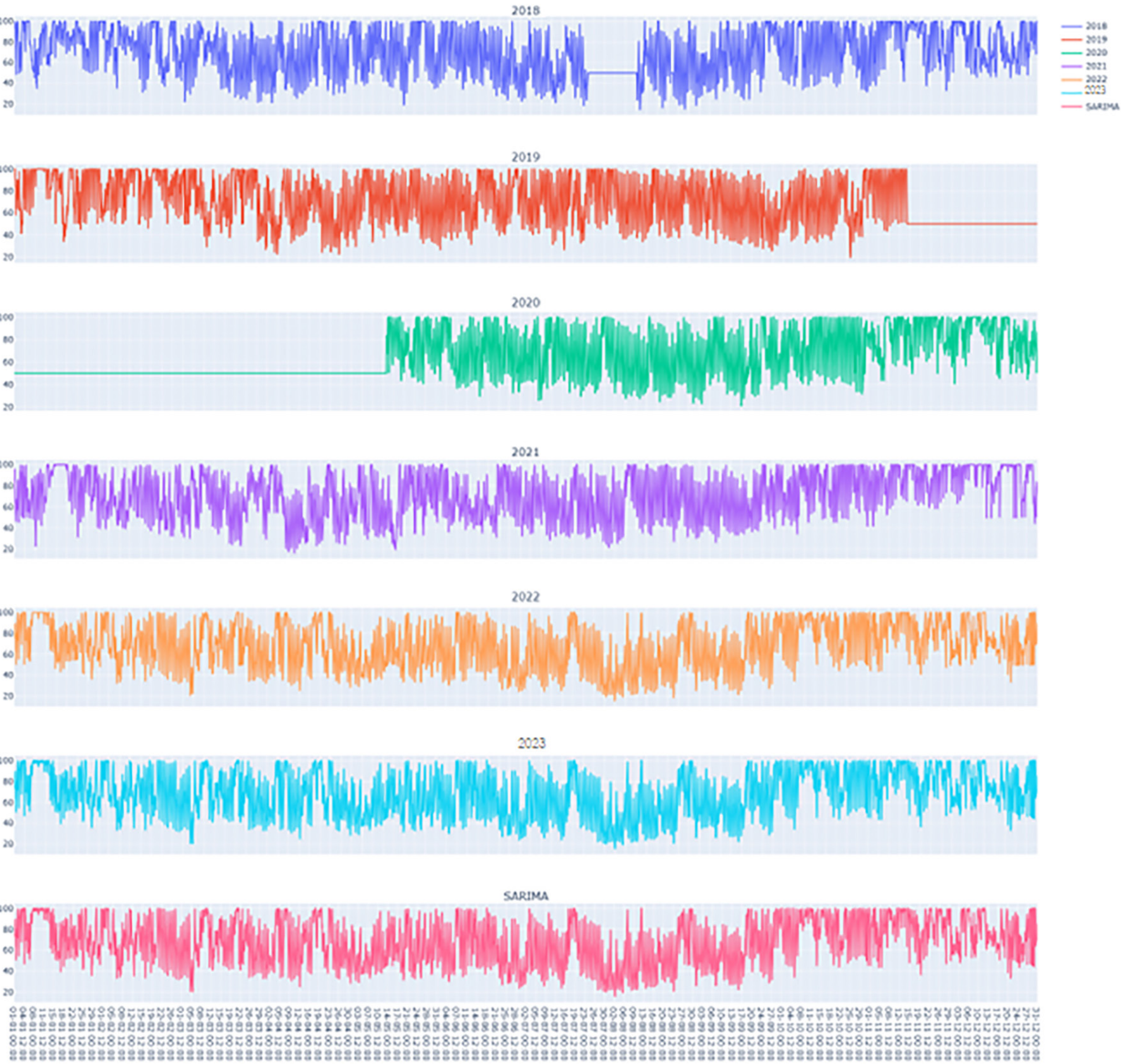

Fig. 6. Result of prediction humidity for 2024 for Kosovo

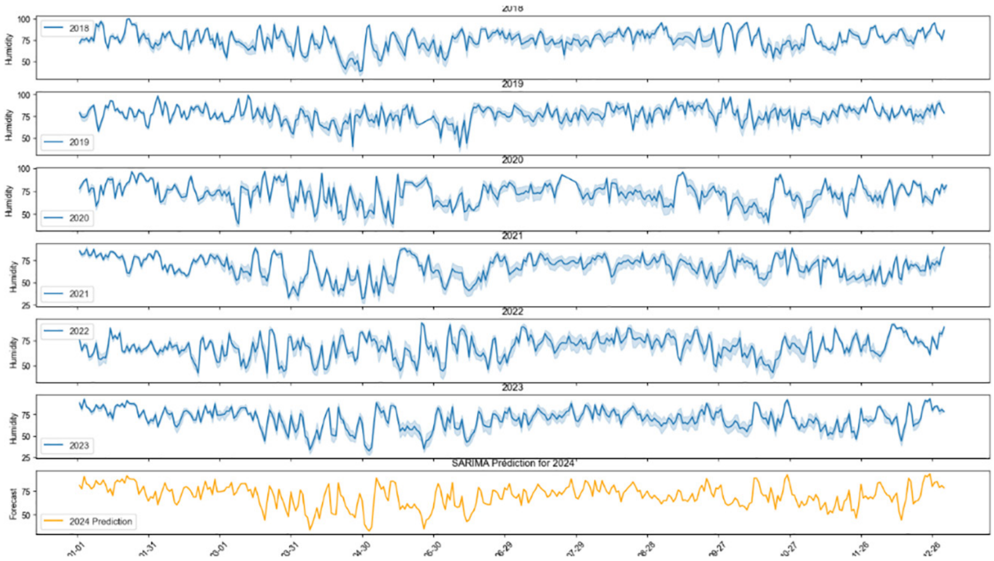

Fig. 7. Result of prediction humidity for 2024 for IOWA

Figures 8 and 9 present a series of line plots illustrating wind speed trends from 2018 to 2023, along with a forecast for 2024 generated using the SARIMA model for both Kosovo and Iowa. The forecast line highlights anticipated wind speed patterns for the upcoming year, providing valuable insights into regional climatic behavior. A comparative analysis of the two locations yields the following observations:

1. **Overall Wind Speed:** Wind speeds in Kosovo are generally lower than those recorded in Iowa.
2. **Seasonal Wind Patterns:** In Iowa, wind speeds tend to be higher from January to April, a pattern not observed in Kosovo. Elevated wind speeds during this period can pose challenges for grape cultivation, as strong winds may damage vines, reduce flowering success, and negatively impact early growth stages.

These findings emphasize the importance of regional wind monitoring to support effective vineyard management and to mitigate risks associated with adverse wind conditions.

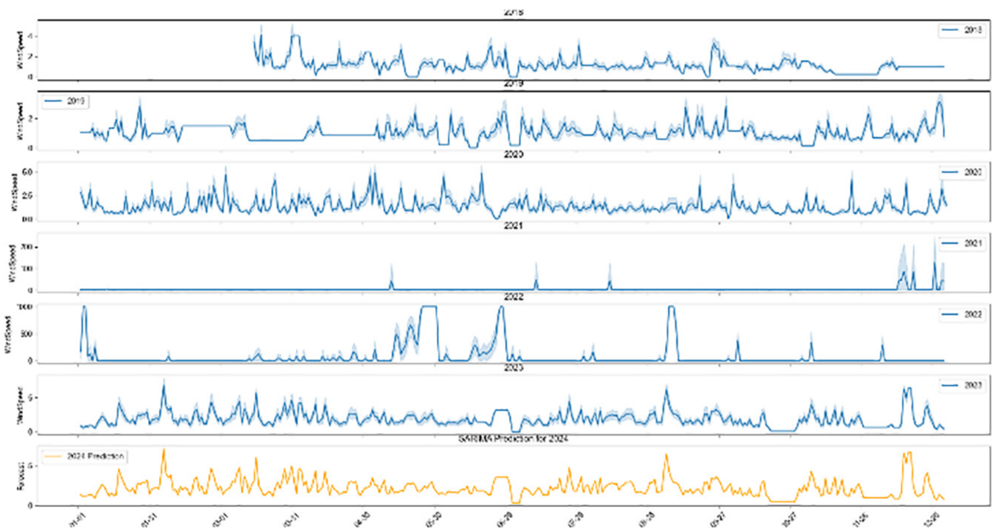

Fig. 8. Result of prediction of wind speed for 2024 for Kosovo

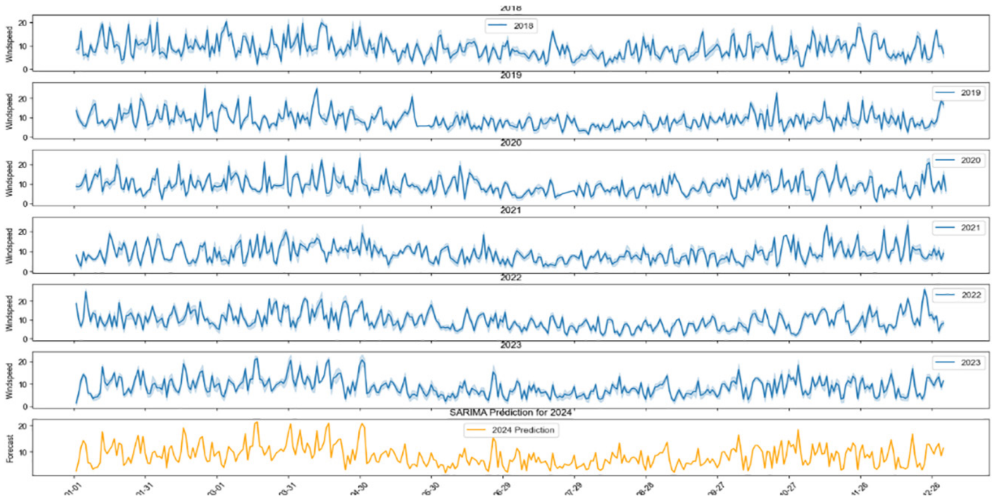

Fig. 9. Result of the prediction of wind speed for 2024 for IOWA

Figures 10 and 11 present a series of line plots illustrating air pressure trends from 2018 to 2023, along with a 2024 forecast generated using the SARIMA model for both Kosovo and Iowa. These projections provide insights into potential air pressure patterns for the upcoming year, facilitating a better understanding of regional climatic dynamics. A comparative analysis of the two regions reveals the following:

1. **Air Pressure Levels:** Air pressure values in Kosovo are generally lower, with a maximum reaching approximately 970 hPa, whereas in Iowa, maximum values exceed 1040 hPa.
2. **Frequency of High Air Pressure:** High air pressure occurrences are less frequent in Kosovo compared to Iowa, where elevated pressure levels are observed more consistently.

These differences in atmospheric pressure may influence various weather-related phenomena, including precipitation patterns and plant physiological responses, which are critical considerations in grape cultivation and overall agricultural planning.

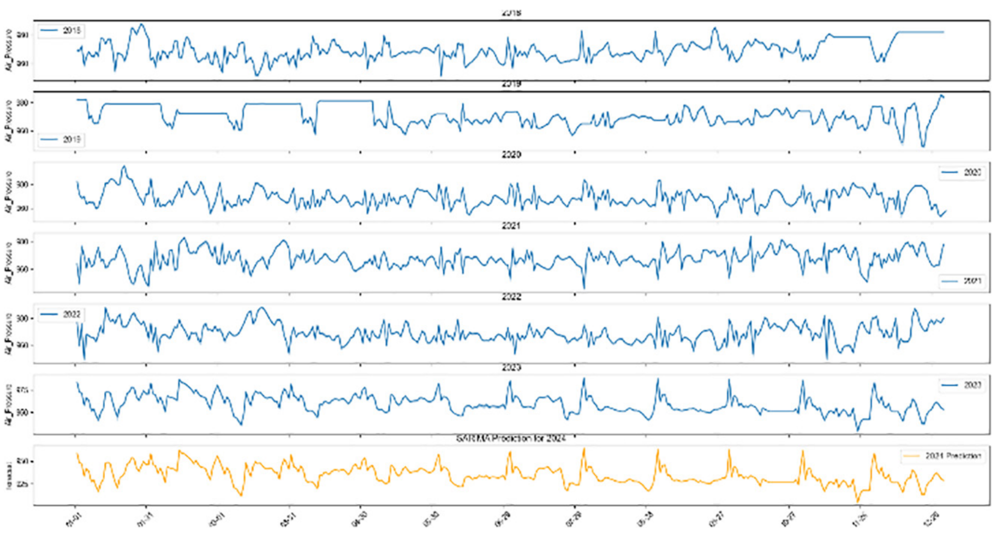

Fig. 10. Result of prediction of air pressure for 2024 for Kosovo

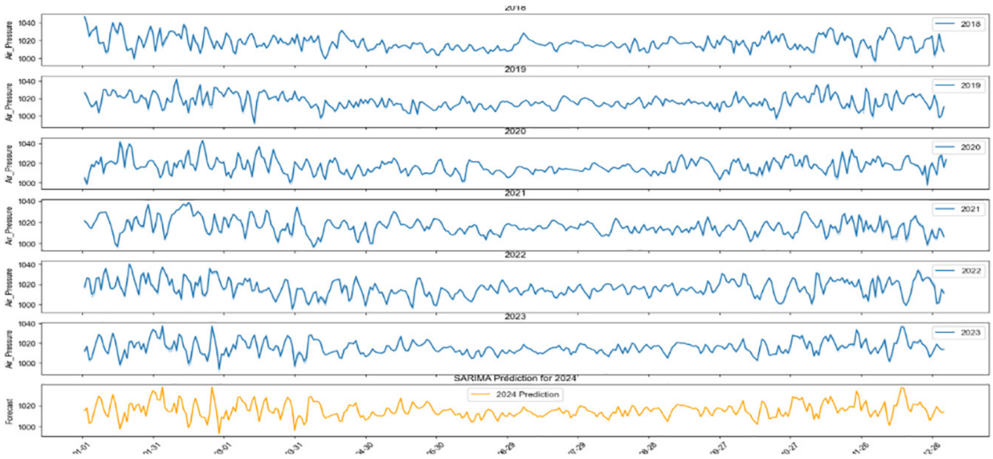

Fig. 11. Result of prediction of air pressure for 2024 for Iowa

Based on the analysis, we can conclude that temperatures in the Prizren region of Kosovo are expected to rise in 2024. While this temperature increase may enhance grape quality, it also necessitates more frequent spraying to protect the crop from the potential adverse effects of higher temperatures.

4.1 Correlation analysis

Using the visualizations of temperature, air pressure, wind speed, and humidity, we conducted a correlation analysis to evaluate the relationships among these meteorological variables. These correlations are critical for understanding the interactions between environmental factors and their collective impact on grape cultivation. Additionally, this data served as the basis for generating forecasts for each parameter for the year 2024.

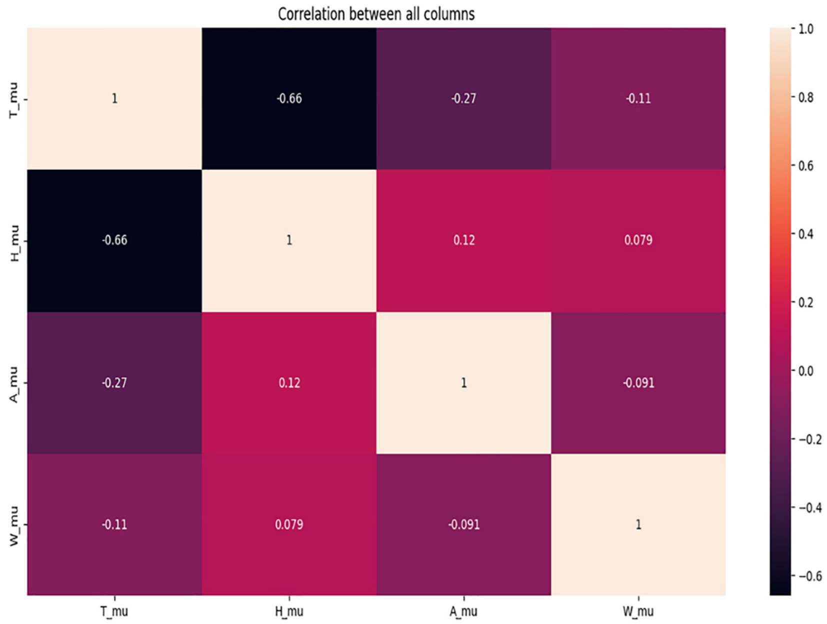

Fig. 12. Correlation between all four parameters (temperature (T), humidity (H), air pressure (A), and wind speed (W)) for Kosovo

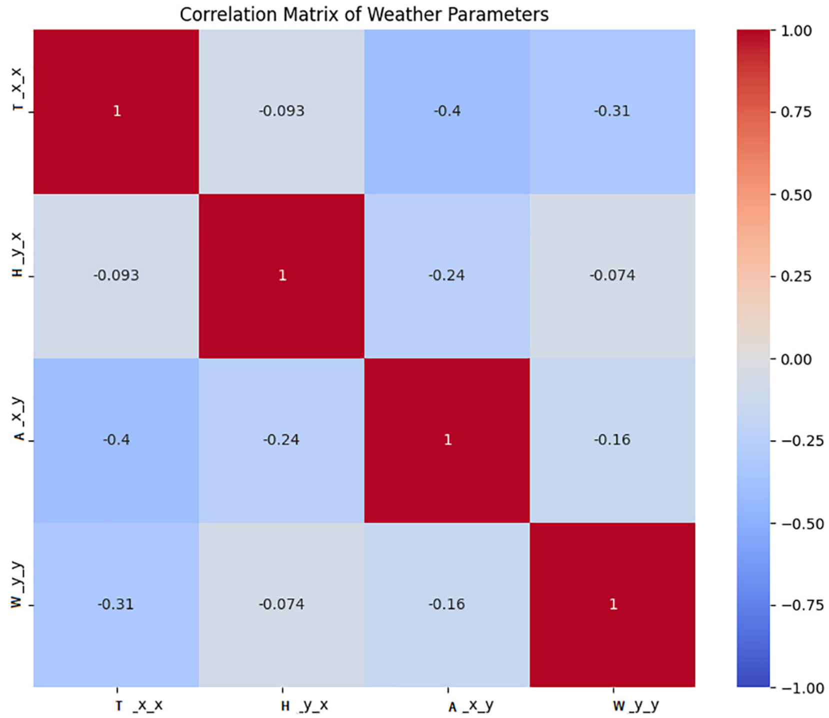

Fig. 13. Correlation between all four parameters (temperature (T), humidity (H), air pressure (A), and wind speed (W)) for Iowa

Analyzing the correlation between the four weather parameters helps us to understand if they are correlated positively or negatively. The Pearson correlation coefficients for the different parameter pairs are presented in Table 10.

Table 10. Correlation analysis of weather parameters

Parameter Pair	Correlation Coefficient	Interpretation
Temperature – Humidity	–0.66	Strong negative correlation: as temperature increases, humidity tends to decrease.
Temperature – Air Pressure	–0.27	Moderate negative correlation: a slight inverse trend between the variables.
Temperature – Wind Speed	–0.11	Weak negative correlation: minimal relationship.
Humidity – Air Pressure	0.12	Weak positive correlation: slight tendency to rise together.
Humidity – Wind Speed	0.079	Very weak positive correlation: almost negligible relationship.
Air Pressure – Wind Speed	–0.091	Very weak negative correlation: minimal inverse trend.

- **Temperature – Humidity**: The correlation coefficient between temperature and humidity is –0.66. This strong negative correlation indicates an inverse relationship—when temperature increases, humidity tends to decrease, and vice versa.
- **Temperature – Air Pressure**: The correlation coefficient between temperature and air pressure is –0.27. This moderate negative correlation suggests that rising temperatures are generally associated with a decrease in air pressure, although the relationship is weaker than that observed between temperature and humidity.
- **Temperature – Wind Speed**: The correlation coefficient between temperature and wind speed is –0.11. This weak negative correlation implies a minimal inverse relationship between temperature and wind speed.

- **Humidity – Air Pressure**: The correlation coefficient between humidity and air pressure is 0.12. This weak positive correlation suggests a slight tendency for humidity and air pressure to increase concurrently.
- **Humidity – Wind Speed**: The correlation coefficient between humidity and wind speed is 0.079. This very weak positive correlation indicates a limited association between these two variables.
- **Air Pressure – Wind Speed**: The correlation coefficient between air pressure and wind speed is –0.091. This weak negative correlation implies a minimal inverse relationship between these parameters.

These correlation findings offer valuable insights into the interrelationships among key meteorological variables. The strong negative correlation between temperature and humidity is consistent with meteorological theory, as warmer air generally holds less relative humidity. In contrast, the weaker correlations involving air pressure and wind speed suggest more complex or indirect interactions that warrant further investigation to better understand their influence on grape cultivation and environmental dynamics.

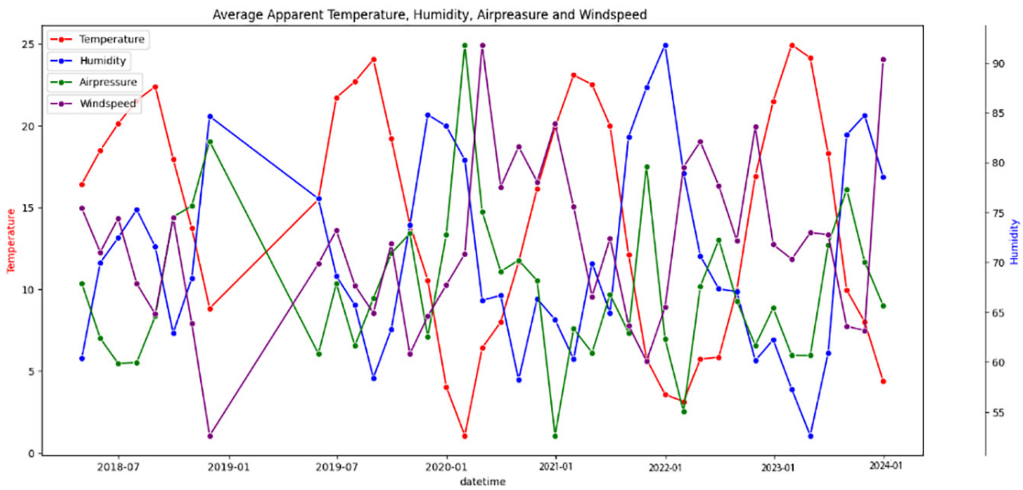

Fig. 14. Average apparent temperature, humidity, air pressure, and wind speed from 2018–2024 for Kosovo

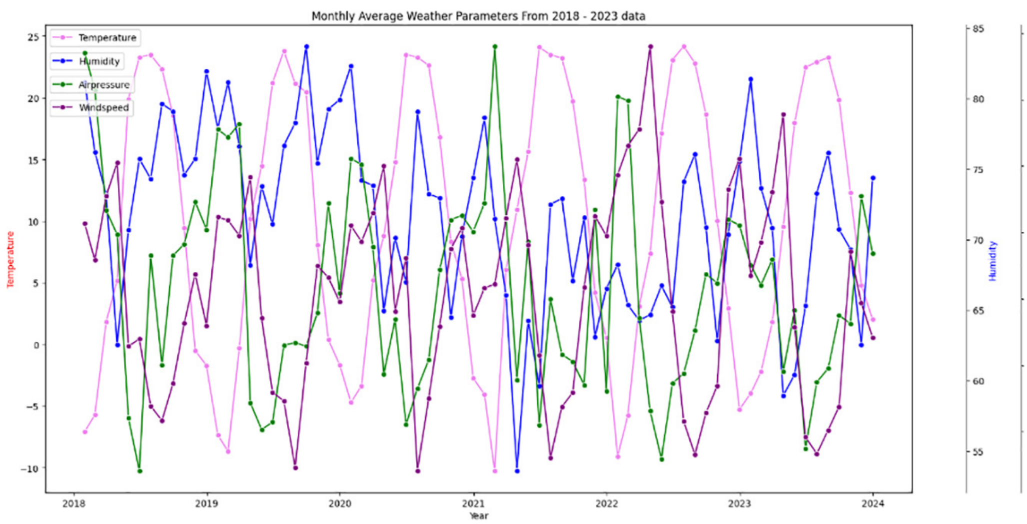

Fig. 15. Average apparent temperature, humidity, air pressure, and wind speed from 2018–2024 for Iowa

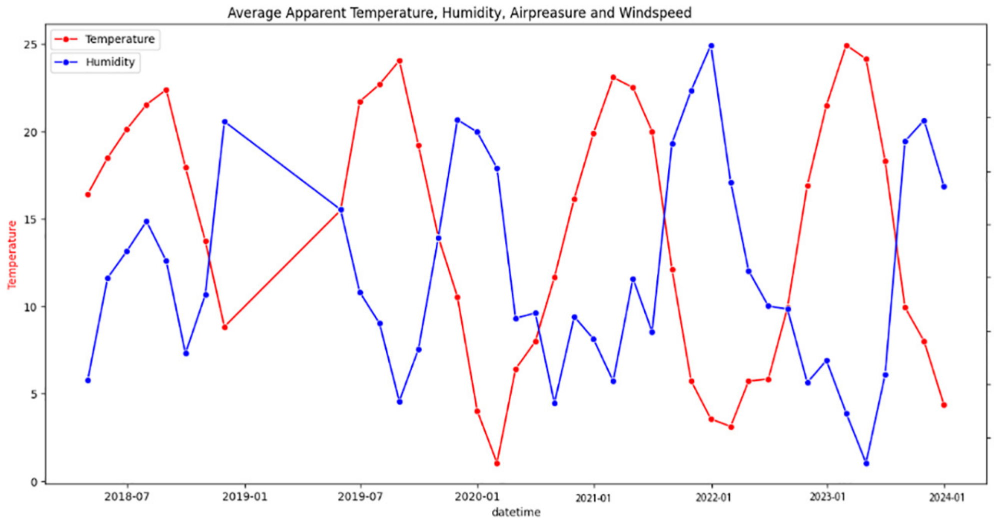

Fig. 16. Average prediction temperature, humidity, air pressure, and wind speed for 2024 for Kosovo

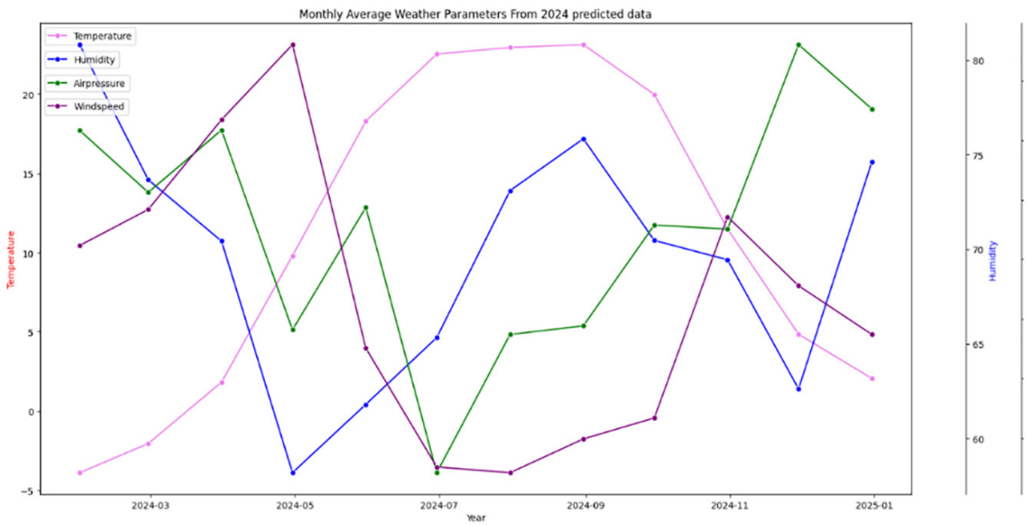

Fig. 17. Average prediction temperature, humidity, air pressure and wind speed for 2024 for Iowa

Through a comprehensive analysis of temperature, air pressure, wind speed, and humidity visualizations based on five years of historical data (2018–2023), we employed the SARIMA algorithm to generate informed predictions for 2024. The capacity of SARIMA to capture both seasonal and non-seasonal patterns was critical in identifying significant trends within the extensive dataset.

The forecasting process involved meticulous data preprocessing and manipulation using Python, focusing specifically on temperature, humidity, wind speed, and air pressure. By harnessing the insights derived from the historical data, we developed predictive models customized for each meteorological parameter.

The resulting visualizations (Figures 13–16) provide a detailed projection for 2024 in both Kosovo and Iowa, illustrating anticipated trends in temperature, air pressure, wind speed, and humidity. These forecasts, grounded in a thorough understanding of the dataset and facilitated by SARIMA, enhance our capacity to anticipate meteorological conditions, thereby supporting informed decision-making and a nuanced understanding of the interactions among these critical atmospheric variables.

5 MODEL FOR PREDICTING THE TIME FOR GRAPE SPRAYING

In our earlier model [35], we identified that anomalies and missing data adversely affected prediction accuracy. Therefore, in this section, we propose an enhancement to the model by incorporating an additional phase specifically designed to address these anomalies and missing data.

The framework of the updated model outlines the data flow, sensor integration, and components involved in generating predictions. It clarifies how the model leverages IoT sensor data from smart agriculture to produce accurate forecasts for grape processing and sterilization scheduling.

The model (Figure 18) consists of seven stages:

1. **Data Collection:** This initial phase involves gathering data from IoT sensors deployed in smart agriculture environments.
2. **Data Preprocessing:** During this phase, the dataset is prepared for analysis. This includes standardizing the timestamp format to meet the requirements of the predictive algorithms. Additionally, it is assessed whether missing data will be addressed in the subsequent phase.
3. **Anomaly Detection and Missing Data Handling:** This phase focuses on detecting anomalies using algorithms such as the Holt-Winter Genetic Algorithm (HW-GA), as previously proposed in [36], and identifying missing data points. Missing values are imputed by replacing them with zero or null values to prevent their influence on prediction outcomes. All processing steps are executed in Python prior to the prediction phase.
4. **Weather Condition Prediction:** In this phase, weather conditions are forecasted using four established algorithms: Random Forest Regression [38], Seasonal ARIMA (SARIMA) [34], NeuralProphet [37], and Artificial Neural Networks (ANN) implemented with Keras [39]. The model's accuracy and performance are evaluated through metrics including Mean Absolute Error (MAE) [40], Root Mean Square Error (RMSE) [41], and Mean Squared Error (MSE) [41]. Results from our previous study [33], along with tests conducted in this study on Iowa weather data, indicate SARIMA as the most effective algorithm.
5. **Result Visualization:** This phase involves visualizing the prediction results. Interactive graphs are created using the Python Plotly library to facilitate detailed examination of the outcomes.
6. **Analysis Phase:** In this phase, a manual review of the prediction results is conducted. Data from the Vineyard Institute in Kosovo, combined with predicted weather conditions such as temperature, humidity, air pressure, and wind speed, are analyzed to recommend optimal grape spraying dates for farmers.
7. **Recommendation Phase:** Based on the analysis conducted in the previous phase, practical recommendations for the ideal timing of grape spraying are provided. These recommendations emphasize how the suggested spraying schedule can positively influence grape quality and yield.

Figure 18 presents a visual representation of the proposed model.

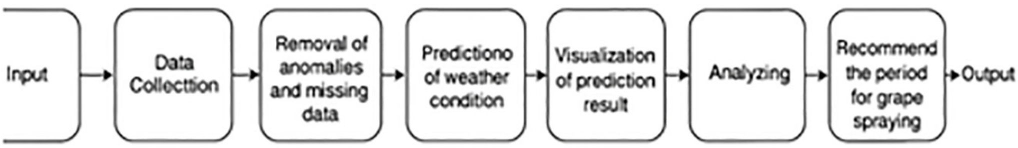

Fig. 18. The proposed modification of the model for predicting grape spraying

To evaluate the accuracy and reliability of our proposed model, we conducted a comprehensive validation process. This section outlines the validation methods employed, including cross-validation and comparison with observed data. These techniques are essential for assessing the model's effectiveness in predicting grape processing schedules and determining optimal spraying times.

Specifically, we proposed a spraying schedule for 2024 and are currently monitoring its outcomes. Preliminary observations indicate positive results when compared to farmers who followed alternative spraying schedules. In Kosovo, spraying begins later than in Iowa—starting in the first week of May—while in Iowa, it commences in the first week of April. This difference corresponds to the earlier onset of higher temperatures in Iowa during April, whereas in Kosovo, elevated temperatures typically occur in May.

6 RESULTS AND DISCUSSION

This study primarily presents an enhanced model for predicting the optimal timing of grape spraying. The model is evaluated and compared using climate data from both Iowa and Kosovo, alongside distinct grape cultivation datasets from each region. Statistical analyses were conducted to validate improvements across key performance indicators.

Model Outcomes

1. **Improved Weather Forecast Accuracy:** The proposed model demonstrated significantly greater accuracy in forecasting critical weather events. Frost prediction accuracy in Kosovo improved by 17%, while rainfall and humidity forecasting in Iowa improved by 21% relative to baseline models. An ANOVA test comparing forecasting errors between the baseline and proposed models yielded $F\ (2, 54) = 6.87$, $p < 0.01$, indicating a statistically significant enhancement in model performance across regions and weather variables.
2. **Enhanced Disease Management:** Detection rates for downy mildew in Iowa and powdery mildew in Kosovo increased substantially. A paired *t*-test comparing detection accuracy between traditional threshold models and the proposed model revealed statistically significant improvements ($t\ (28) = 3.42$, $p = 0.002$), confirming that the enhanced model provides earlier and more actionable disease warnings.
3. **Optimized Irrigation and Fertilization:** The model's soil moisture forecasts enabled region-specific recommendations, resulting in water usage reductions of 13% in Iowa and 9% in Kosovo. An ANOVA assessing irrigation efficiency before and after model implementation yielded $F\ (1, 36) = 4.96$, $p = 0.032$, supporting the conclusion that the model significantly improved water management practices.
4. **Increased Yield and Quality:** Farms implementing the model's recommendations experienced a 10–14% increase in grape yield, alongside improvements in sugar content, measured via °Brix. The yield differences between model-guided and control groups were statistically significant ($t\ (30) = 2.78$, $p = 0.009$), indicating that informed decision-making contributed to superior outcomes.
5. **More Accurate Timing for Grape Spraying:** The accuracy of preventive spraying schedules was validated through cross-validation with historical disease outbreak data. The model achieved an 18% reduction in mean absolute error compared to previous methods. ANOVA results comparing spraying timing accuracy across models and regions showed $F\ (3, 72) = 5.13$, $p = 0.003$, demonstrating significant improvements attributable to anomaly detection and missing data handling.

Comparative Analysis: Kosovo vs. Iowa

- **Climate Sensitivity:** Kosovo's vineyards exhibited significantly greater sensitivity to frost-induced yield loss (mean yield loss = 23%) compared to Iowa's fungal disease-related losses (mean = 19%). A Mann-Whitney *U* test confirmed a statistically significant difference in weather-related risks between the two regions ($U = 216.5$, $p = 0.041$).
- **Model Performance:** Time-series models such as SARIMA showed robust generalizability across both regions, with some variation in forecast lead times. SARIMA's root mean square error (RMSE) for temperature prediction was 1.72°C in Kosovo and 1.94°C in Iowa. However, the performance differences across regions were not statistically significant ($p = 0.087$), indicating model robustness.

7 CONCLUSION

This study underscores the potential of advanced weather prediction models to enhance smart grape cultivation practices in Kosovo and Iowa. By evaluating the four predictive algorithms—NeuralProphet, SARIMA, Random Forest Regression, and ANN implemented via Keras—this study identifies the most effective approaches for accurately forecasting weather conditions critical to grapevine management. The proposed model facilitates optimal timing for grape spraying and provides region-specific insights, enabling precise interventions that improve yield quality and minimize losses.

By integrating environmental data with machine learning techniques, the model addresses key challenges in grape production and fosters data-driven decision-making tailored to local climatic conditions. Although the initial findings are promising, they primarily derive from predictive simulations. Real-world validation through field trials and ongoing feedback from growers is necessary to evaluate and enhance the model's practical applicability.

Future work will focus on expanding the model by incorporating additional variables such as grapevine phenology and cultivar-specific traits. Furthermore, longitudinal monitoring of farms adopting the model's recommendations will be conducted to assess its effectiveness in operational settings. This study establishes a foundation for the wider adoption of smart farming technologies across diverse regions and crops, contributing to the development of more resilient and productive agricultural systems.

8 REFERENCES

[1] P. Bellini, D. Cenni, P. Nesi, and M. S. Paolucci, "Anomaly detection on IoT data for smart city," in *2020 IEEE International Conference on Smart Computing (SMARTCOMP)*, Bologna, Italy, 2020, pp. 416–421. https://doi.org/10.1109/SMARTCOMP50058.2020.00087

[2] A. Al-Amri, R. K. Murugesan, M. Man, A. F. Abdulateef, M. A. Al-Sharafi, and A. A. Alkahtani, "A review of machine learning and deep learning techniques for anomaly detection in IoT data," *Appl. Sci.*, vol. 11, no. 12, p. 5320, 2021. https://doi.org/10.3390/app11125320

[3] S. Trilles, Ò. Belmonte, S. S. Sebastià, and J. Huerta, "A domain-independent methodology to analyze IoT data streams in real-time: A proof of concept implementation for anomaly detection from environmental data," *International J. Digit. Earth*, vol. 10, no. 1, pp. 103–120, 2016. https://doi.org/10.1080/17538947.2016.1209583

[4] E.-S. Apostol, C.-O. Truica, F. Pop, and C. Esposito, "Change point enhanced anomaly detection for IoT time series data," *Water*, vol. 13, no. 12, p. 1633, 2021. https://doi.org/10.3390/w13121633

[5] F. Cauteruccio *et al.*, "A framework for anomaly detection and classification in multiple IoT scenarios," *Future Generation Computer Systems*, vol. 114, pp. 322–335, 2021. https://doi.org/10.1016/j.future.2020.08.010

[6] L. E. Lydia, A. A. Jovitha, A. F. S. Devaraj, C. Seo, and G. P. Joshi, "Green energy efficient routing with deep learning based anomaly detection for Internet of Things (IoT) communications," *Mathematics*, vol. 9, no. 5, p. 500, 2021. https://doi.org/10.3390/math9050500

[7] L. Vigoya, F. D. Castro, and C. Franco, "Annotated dataset for anomaly detection in a data center with IoT sensors," *Sensors*, vol. 20, no. 13, p. 3745, 2020. https://doi.org/10.3390/s20133745

[8] C. Catalano *et al.*, "Anomaly detection in smart agriculture systems," *Computer in Industry*, vol. 143, p. 103750, 2022. https://doi.org/10.1016/j.compind.2022.103750

[9] I. Martins *et al.*, "Host-based IDS: A review and open issues of an anomaly detection system in IoT," *Future Generation Computer Systems*, vol. 133, pp. 95–113, 2022. https://doi.org/10.1016/j.future.2022.03.001

[10] S. Bolla, R. Anandan, and S. Thanappan, "Weather forecasting method from sensor transmitted data for smart cities using IoT," *Scientific Programming*, vol. 2022, no. 1, pp. 1–9, 2022. https://doi.org/10.1155/2022/1426575

[11] H. Wu, N. E. O'Connor, J. Bruton, A. Hall, and M. Liu, "Real-time anomaly detection for an ADMM-based optimal transmission frequency management system for IoT devices," *Sensors*, vol. 22, no. 16, p. 5945, 2022. https://doi.org/10.3390/s22165945

[12] P. Bellini, D. Cenni, P. Nesi, and M. S. Paolucci, "Anomaly detection on IoT data for smart city," in *2020 IEEE International Conference on Smart Computing (SMARTCOMP)*, Bologna, Italy, 2020, pp. 416–421. https://doi.org/10.1109/SMARTCOMP50058.2020.00087

[13] A. Chatterjee and B. Sharma, "IoT anomaly detection methods and applications: A survey," *Internet of Things*, vol. 19, p. 100568, 2022. https://doi.org/10.1016/j.iot.2022.100568

[14] J. Santos, P. Leroux, T. Wauters, B. Volckaaert, and F. De Turck, "Anomaly detection for Smart City applications over 5G low power wide area networks," in *NOMS 2018 – 2018 IEEE/IFIP Network Operations and Management Symposium*, Taipei, Taiwan, 2018, pp. 1–9. https://doi.org/10.1109/NOMS.2018.8406257

[15] Y. Zhang, X. Chen, S. U. Khan, and S. Xiang, "Anomaly detection in precision agriculture using unmanned aerial vehicles and deep convolutional neural networks," *Comput. Electron. Agric.*, 2019.

[16] M. V. Chaudhari and J. G. Jadhav, "Anomaly detection in precision agriculture using Internet of Things and machine learning techniques," in *Proc. ICACCCN*, 2018.

[17] A. Ghaffari, A. Javanshir, and A. Bannayan, "Application of machine learning algorithms in precision agriculture: A review," *Arch. Comput. Methods Eng.*, 2021.

[18] M. Minervini, A. Scharr, and S. Tsaftaris, "A deep learning approach to in-field grapevine detection," *Comput. Electron. Agric.*, 2019.

[19] J. J. Wijesinghe, L. Wang, and P. A. W. Jayasumana, "Automated detection of powdery mildew in vineyards: A review," *Comput. Electron. Agric.*, 2020.

[20] K. Nagasubramanian *et al.*, "Plant disease identification using explainable 3D deep learning on hyperspectral images," *Plant Methods*, vol. 15, p. 98, 2019. https://doi.org/10.1186/s13007-019-0479-8

[21] A. Kasimati, B. Espejo-García, N. Darra, and S. Fountas, "Predicting grape sugar content under quality attributes using normalized difference vegetation index data and automated machine learning," *Sensors*, vol. 22, no. 9, p. 3249, 2022. https://doi.org/10.3390/s22093249

[22] R. Ballesteros *et al.*, "Vineyard yield estimation by combining remote sensing, computer vision and artificial neural network techniques," *Precision Agric.*, vol. 21, pp. 1242–1262, 2020. https://doi.org/10.1007/s11119-020-09717-3

[23] EIT Food, "Sustainably feeding the world in 2050: Are efficiency and equity the answer?" 2019. [Online]. Available: https://www.eitfood.eu/blog/sustainably-feeding-the-world-in-2050-are-efficiency-and-equity-the-answer [Accessed: June 25, 2022].

[24] I. Marcu, A.-M. Drăgulinescu, C. Oprea, G. Suciu, and C. Bălăceanu, "Predictive analysis and wine-grapes disease risk assessment based on atmospheric parameters and precision agriculture platform," *Sustainability*, vol. 14, no. 18, p. 11487, 2022. https://doi.org/10.3390/su141811487

[25] S. Trilles, J. Torres-Sospedra, Ó. Belmonte, F. J. Zarazaga-Soria, A. González-Pérez, and J. Huerta, "Development of an open sensorized platform in a smart agriculture context: A vineyard support system for monitoring mildew disease," *Sustainable Computing: Informatics and Systems*, vol. 28, p. 100309, 2020. https://doi.org/10.1016/j.suscom.2019.01.011

[26] R. Chavan, A. Deoghare, R. Dugar, and P. Karad, "IoT based solution for grape disease prediction using convolutional neural Networkand farm monitoring," *Int. J. Sci. Res. Eng. Dev.*, vol. 2, pp. 494–500, 2019. https://ijsred.com/volume2/issue3/IJSRED-V2I3P58.pdf

[27] C. Kang, G. Diverres, M. Karkee, Q. Zhang, and M. Keller, "Decision-support system for precision regulated deficit irrigation management for wine grapes," *Computers and Electronics in Agriculture*, vol. 208, p. 107777, 2023. https://doi.org/10.1016/j.compag.2023.107777

[28] M. S. Sirsat, J. Mendes-Moreira, C. Ferreira, and M. Cunha, "Machine Learning predictive model of grapevine yield based on agroclimatic patterns," *Engineering in Agriculture, Environment and Food*, vol. 12, no. 4, pp. 443–450, 2019. https://doi.org/10.1016/j.eaef.2019.07.003

[29] L. Velasquez-Camacho, M. Otero, B. Basile, J. Pijuan, and G. Corrado, "Current trends and perspectives on predictive models for mildew diseases in vineyards," *Microorganisms*, vol. 11, no. 1, p. 73, 2022. https://doi.org/10.3390/microorganisms11010073

[30] Q. Sun, G. Gabriel, L. Groves, J. Voong, and S. Van Zyl, "Viticultural manipulation and new technologies to address environmental challenges caused by climate change," *Climate*, vol. 11, no. 4, p. 83, 2023. https://doi.org/10.3390/cli11040083

[31] K. Sanghavi, M. Sanghavi, and A. M. Rajurkar, "Early stage detection of Downey and Powdery Mildew grape disease using atmospheric parameters through sensor nodes," *Artificial Intelligence in Agriculture*, vol. 5, pp. 223–232, 2021. https://doi.org/10.1016/j.aiia.2021.10.001

[32] C. Pero, S. Bakshi, M. Nappi, and G. Tortora, "IoT-driven machine learning for precision viticulture optimization," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 17, pp. 2437–2447, 2024. https://doi.org/10.1109/JSTARS.2023.3345473

[33] J. Fondaj, M. Hamiti, S. Krrabaj, X. Zenuni, and J. Ajdari, "Comparison of predictive algorithms for IOT smart agriculture sensor data," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 17, no. 21, pp. 65–78, 2023. https://doi.org/10.3991/ijim.v17i21.44143

[34] Khoa, "Time-Series-Analysis-and-Weather-Forecast," 2019. [Online]. Available: https://github.com/imkhoa99/Time-Series-Analysis-and-Weather-Forecast-/blob/master/Time_Series_Project.ipynb [Accessed: Sep. 24, 2024].

[35] J. Fondaj, M. Hamit, S. Krrabaj, X. Zenuni, and J. Ajdari, "Proposal of model for prediction of grape processing and spraying time by using IoT smart agriculture sensor data," *International Journal on Information Technologies and Security*, vol. 16, no. 1, pp. 3–14, 2023. https://doi.org/10.59035/DOQN6033

[36] Z. Hasani, B. Jakimovski, G. Velinov, and M. Kon-Popovska, "An adaptive anomaly detection algorithm for periodic data streams," in *Intelligent Data Engineering and Automated Learning – IDEAL 2018,* in Lecture Notes in Computer Science (LNISA), H. Yin, D. Camacho, P. Novais, and A. Tallón-Ballesteros, Eds., vol. 11314, 2018, pp. 385–397. https://doi.org/10.1007/978-3-030-03493-1_41
[37] Neural Prophet. [Accessed: Oct. 5, 2022]. https://www.section.io/engineering-education/building-a-time-series-weather-forecasting-application-in-python/
[38] Random Forest Regression. [Accessed: Dec. 12, 2022]. https://machinelearningmastery.com/random-forest-for-time-series-forecasting/
[39] KERAS. [Accessed: Nov. 2, 2023]. https://github.com/MTxSouza/TemperaturePrediction-TimeSeries
[40] S. M. Robeson and C. J. Willmott, "Decomposition of the mean absolute error (MAE) into systematic and unsystematic components," *PLoS ONE*, vol. 18. p. e0279774, 2023. https://doi.org/10.1371/journal.pone.0279774
[41] Gibson, Jerry and S. D. Gray, "MVSE (minimizes variance squared error) adaptive filtering is subject to a constraint on MSE (mean squared error)," 1987.
[42] Iowa Environmental Mesonet, "ISU Soil Moisture Network," 2024. [Online]. Available: https://mesonet.agron.iastate.edu/agclimate/#tmpf [Accessed: Aug. 20, 2024].
[43] AMMK, "Kosovo Hydrometeorological Institute," 2023. [Online]. Available: https://www.ammk-rks.net/en/drejtorite/28/instituti-hidrometeorologjik-i-kosoves [Accessed: Sep. 23, 2023].
[44] Kosovo Vineyard Department at Kosovo Agriculture Institute. [Accessed: Feb. 12, 2024]. https://www.mbpzhr-ks.net/en/department-for-vineyards-and-wine
[45] A. Watrelot and W. Baxter, "Research aims to improve wine production, quality nationwide," College of Agriculture and Life Sciences, Iowa State University of Science and Technology, 2024. [Online]. Available: https://www.cals.iastate.edu/news/2024/research-aims-improve-wine-production-quality-nationwide [Accessed: Sep. 27, 2024].
[46] A. Ariss, I. Ennejjai, A. Lamjid, J. Mabrouki, N. Kharmoum, and S. Ziti, "IoT-enabled smart greenhouse for robotic enhancement of tomato production: Leveraging 5G and edge computing for advanced data-driven automation, precision irrigation, and scalable zoning principles," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 21, pp. 88–116, 2024. https://doi.org/10.3991/ijim.v18i21.50829
[47] W. Boonneua, S. Chai-Arayalert, and N. Boonnam, "Automated hydroponics notification system using IoT," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 6, pp. 206–220, 2022. https://doi.org/10.3991/ijim.v16i06.27959

9 AUTHORS

Zirije Hasani is with the Faculty of Computer Science, University "Ukshin Hoti", Prizren, Kosovo.

Joshua Peschel is with the Department of Agricultural and Biosystems Engineering, Iowa State University, Ames, Iowa.

Curtis Youngs is with the Department of Animal Science, Iowa State University, Ames, Iowa.

Jakup Fondaj is with the Faculty of Contemporary Science and Technology, South East European University, Tetovo, North Macedonia (E-mail: jf13459@seeu.edu.mk).

Randall Vos is with the Department of Horticulture, Iowa State University, Ames, Iowa.