Comparative Analysis of Soil Moisture Interpolation Techniques in Apple Orchards of Trentino Region

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***Abstract*—This paper provides valuable insights into the application of spatial interpolation techniques in smart agriculture and highlights the potential for further improvements through the integration of advanced geostatistical models. Specifically, it evaluates and compares two spatial interpolation techniques, Inverse Distance Weighting and Ordinary Kriging, for estimating soil moisture in apple orchards located in the Val di Non region of Trentino, Italy. Data were gathered from 18 tensiometer sensors deployed across the apple orchards, providing continuous soil moisture measurements over a specified time frame in 2023. The accuracy of both interpolation methods was assessed using root mean square error as the primary evaluation metric, with various validation methods employed to ensure robustness. Additionally, statistical analyses were conducted to determine the significance of differences in performance between the methods. The results indicate that Inverse Distance Weighting, despite its computational efficiency, slightly outperforms Ordinary Kriging in terms of accuracy, with statistically significant lower error values, making it a preferable choice for real-time soil moisture mapping and precision irrigation management in the region.**

***Index Terms*—Smart Agriculture, Soil moisture mapping, Irrigation efficiency, Geostatistics, Inverse Distance Weighting, Ordinary Kriging.**

I. Introduction

The increasing global emphasis on sustainable agricultural practices requires advanced precision farming methods to optimize resource use, improve crop yields, and preserve soil health. Soil moisture is one of the most critical components of the agricultural ecosystem, as it directly impacts plant growth, irrigation efficiency, and overall farm productivity [1].

Efficient monitoring and management of soil moisture are essential for determining optimal irrigation schedules, reducing water waste, and promoting plant health, especially in high-value crops. One of the emerging needs in precision agriculture is the ability to collect fine-grained, real-time data from the field using cost-effective but reliable Internet of Things (IoT) sensors [2]. These sensors can monitor a wide range of environmental variables, including soil moisture, temperature, and humidity, providing farmers with detailed insights into their fields' conditions. By deploying a dense network of such IoT devices across agricultural fields, farmers can achieve a more precise and localized understanding of soil moisture dynamics [3]. The affordability and reliability of modern IoT sensors allow for widespread deployment, making it feasible to support advanced analytics and decision-making [4].

However, obtaining accurate soil moisture data across large agricultural areas remains a challenge since moisture measurements are typically gathered from discrete points. To address this, spatial interpolation techniques are often employed to estimate data at unsampled locations, allowing for the creation of comprehensive distribution maps over extensive areas [5]. This paper specifically focuses on comparing two well-established spatial interpolation methods, namely Inverse Distance Weighting (IDW) and Ordinary Kriging (OK), for estimating soil moisture levels in apple orchards located in the Val di Non region of Trentino, Italy (see Fig. 1).

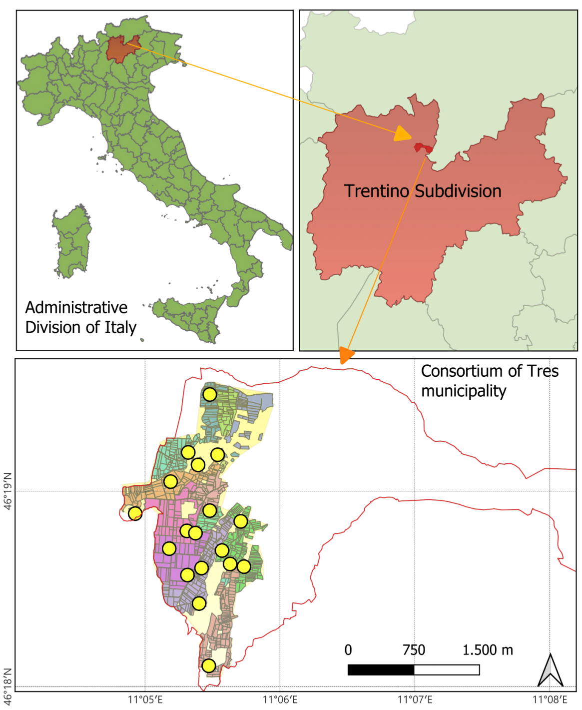

Fig. 1. Geography of the Study Area

The data were gathered from an IoT network of tensiometer sensors strategically deployed across the fields to monitor soil moisture variations. These battery-powered devices provided real-time data essential for understanding water availability in apple orchards, which are highly sensitive to fluctuations in soil moisture [6]. Indeed, accurate soil moisture estimation is of paramount importance in precision agriculture as it helps farmers implement optimal irrigation strategies, preventing both water shortages and excesses, which can have detrimental effects on crop yield and quality

[7]. Notably, recent comparative studies related to soil moisture interpolation were mainly carried out on regions in China and have shown that simpler methods can sometimes outperform more sophisticated geostatistical approaches [8]. The findings from this work are expected to provide valuable insights to farmers, agronomists, and agricultural managers in the Trentino region, enabling them to make informed decisions regarding water management and irrigation practices. By identifying the most effective interpolation technique, this research aims to improve the efficiency of water usage in apple orchards, contributing to more sustainable agricultural practices. Additionally, the study serves as an important case in the ongoing effort to integrate data analysis and geostatistical methods into routinary smart farming initiatives.

The remainder of this paper is organized as follows: Sec. II details the data collection process, including the deployment of tensiometers and the pre-processing steps taken to ensure data quality. Sec. III introduces the methodology, explaining the theoretical basis of the interpolation techniques and the validation methods used to compare their performance. In Sec. IV, the results of the analysis are presented, highlighting the comparative performance of the interpolation techniques based on RMSE and other statistical metrics. Finally, Sec. V concludes the study, summarizing the key takeaways and suggesting directions for future research in soil moisture interpolation and smart farming technologies.

II. Data Collection and Preparation

The sensor deployment took place in the municipality of Tres (Val di Non, Trentino, Italy), where 18 tensiometer sensors were strategically positioned and geo-referenced within apple orchards to monitor soil moisture, as shown in Fig. 1. These sensors, installed at a depth of 30 centimeters, recorded soil moisture levels in millibars (mbar) at 15-minute intervals, generating approximately four readings per hour. The data collection campaign spanned from January 1, 2023, to December 31, 2023. For the purposes of this study, the period from July 15 to July 31, 2023, was selected as optimal because all 18 sensors consistently delivered accurate and continuous measurements during this time. Soil moisture values during this period ranged from approximately 15 mbar to 650 mbar, a significant range given that typical irrigation thresholds for crops fall between 200 mbar (lower, wet limit) and 400 mbar (upper, dry limit).

All data sampled and transmitted by the tensiometers to a cloud-based IoT platform were subjected to temporal alignment and aggregation to ensure consistency, as each tensiometer recorded its readings using local timestamps. The alignment process ensured that each tensiometer produced a measurement at the top of every hour, achieved by averaging the multiple readings collected within each hour to derive a representative soil moisture value. To address missing data points, linear interpolation was applied. Specifically, if a sensor recorded values at two specific moments but lacked data for an intermediate time, the missing value was estimated as the average of the two known values. This imputation technique was implemented after temporal alignment and aggregation, filling any gaps in the hourly data for each sensor. This comprehensive preprocessing approach ensured the dataset was continuous, consistent, and suitable for accurate soil moisture analysis and spatial interpolation.

Following preprocessing, the selected timeframe yielded 408 observations per sensor (17 days $\times$ 24 hours), creating a robust dataset for further analysis. To provide an overview of the data following preprocessing, Fig. 2 presents the time series of daily average values from four selected tensiometers.

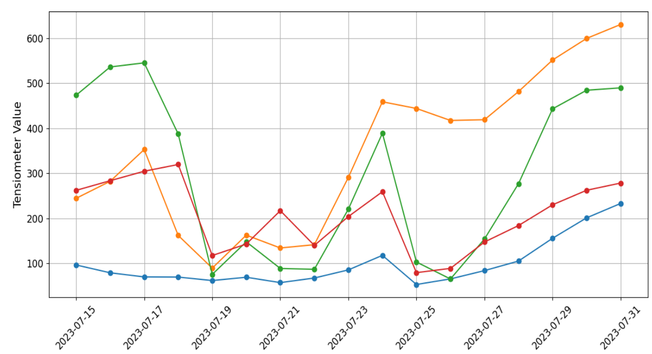

Fig. 2. Time series of daily average soil moisture values from a sample of four tensiometers deployed in the study area.

As observed, the tensiometers' readings exhibit significant variation throughout the period. This is mainly attributed to differing irrigation schedules across the consortium's areas and the soil's non-linear properties, which influence its water absorption capacity. For the sake of completeness, Table I presents descriptive statistics for the 18 time series of tensiometers values analyzed in the study, ordered by their average values over the period considered.

TABLE I
Descriptive Statistics for Sensor Data

ID	mean	median	min	max	std
1	46.41	45.00	28.00	75.75	9.33
2	62.16	56.00	26.33	178.25	23.70
3	63.78	46.00	24.00	242.00	46.61
4	77.49	53.00	22.00	251.00	56.45
5	98.60	83.00	14.50	261.50	56.54
6	105.87	98.00	29.00	250.00	52.65
7	116.13	73.00	26.50	482.67	102.25
8	116.96	88.00	50.00	371.00	71.09
9	117.62	67.88	27.00	464.00	110.73
10	124.41	111.00	25.00	352.75	71.85
11	125.42	85.00	24.25	388.00	103.03
12	126.28	58.25	25.67	530.67	133.48
13	147.26	83.00	33.50	541.00	146.07
14	185.54	123.50	30.00	562.25	148.75
15	207.32	219.12	48.00	361.00	81.24
16	292.41	306.00	29.75	577.25	193.92
17	293.63	384.00	23.50	448.00	143.49
18	345.04	390.12	58.50	651.00	177.69

III. METHODOLOGY

This section describes the details of the interpolation methods used for the analysis, as well as the validation tools employed to compare their results on the dataset discussed in the previous section.

A. Interpolation methods

Spatial interpolation techniques are essential in precision agriculture for estimating values at unsampled (*i.e.*, unknown) locations by leveraging existing observations. In essence, these methods transform discrete measurements into continuous surface maps, enabling a comprehensive understanding of key variables such as soil moisture. By applying interpolation to soil moisture data, farmers and agricultural managers gain a more complete view of moisture distribution across their fields. This supports informed decision-making and contributes to more sustainable, water-conserving agricultural practices [9].
A spatial interpolation problem involves estimating the value of a variable at an unknown location y based on known values at N points x_i. Formally, given a set of known points $x_1, x_2, ..., x_N$, with corresponding values $f(x_1), f(x_2), ..., f(x_N)$, the objective is to find an interpolation function $\hat{f}(y)$ that approximates the value of the variable at the unknown point y. This function depends on the values at the known points $f(x_i)$, typically using a model.
Various techniques exist in the literature while, for this study, two approaches were considered: Inverse Distance Weighting (IDW) and Ordinary Kriging (OK). Both methods are widely used in precision agriculture due to their balance of simplicity and computational efficiency [10]. In brief, IDW is a deterministic method that estimates unknown values by assigning weights to nearby measured points based on their distance, with closer points having more influence on the prediction. On the other hand, OK is a more advanced geostatistical technique that considers both the distance between data points and their spatial autocorrelation. By modeling the spatial relationships in the data, it can produce more refined and potentially more accurate predictions. More in detail, IDW interpolation equation is given by the function $\hat{f}_{IDW}(y)$ as:

$$\hat{f}_{IDW}(y) = \frac{\sum_{i=1}^{N} \frac{f(x_i)}{d(y,x_i)^p}}{\sum_{i=1}^{N} \frac{1}{d(y,x_i)^p}} \tag{1}$$

where $d(y, x_i)$ is the distance between point y and point x_i, and p is the power parameter that controls the weights of the distances.

IDW is a popular choice in the literature due to its straightforward implementation and its ability to generate smooth, continuous surface maps. Its simplicity makes it particularly attractive for applications in precision agriculture where timely and computationally efficient methods are required. However, the performance of IDW can be highly sensitive to certain factors, particularly the choice of the power parameter p and the spatial distribution of the input data. In this study, the parameter was set to $p = 2$, implementing a quadratic weighting scheme that gives significantly more influence to nearby points, as commonly recommended in the literature [11].

The other method considered in the study is Ordinary Kriging (OK), which is the most commonly used version of the Kriging variants. With respect to the previous method, it is slightly more sophisticated, as it assumes that the value of a variable at a given location is a combination of a deterministic trend and a spatially correlated random component. This random component is captured through spatial correlation, which is modeled by the *variogram*. The variogram is a key function in Kriging that describes how the variance between pairs of observations changes with distance [5]. The variogram for a distance h is defined in terms of expected value as:

$$\gamma(h) = \frac{1}{2} E\left[(f(x_i) - f(x_j))^2\right] \tag{2}$$

This definition expresses how much the values differ as the distance h between the points increases, with smaller differences indicating stronger spatial correlation. Then, the general interpolation equation for Ordinary Kriging is given by the function $\hat{f}_{OK}(y)$ as:

$$\hat{f}_{OK}(y) = \sum_{i=1}^{N} \lambda_i f(x_i) \tag{3}$$

where λ_i are the Kriging weights assigned to the known points x_i; this parameters are determined by solving a system of linear equations based on the variogram.

The process to apply Ordinary Kriging it involves three key steps, which are summarized in the following:

1) calculate the empirical variogram from the observed data, assessing the variance of data pairs at varying distances;
2) fit a theoretical variogram model (*e.g.*, spherical, exponential, or Gaussian) to the empirical variogram to capture the spatial structure;
3) use the variogram model to solve the Kriging system and estimate values at unsampled locations, providing unbiased predictions with minimized variance.

Overall, Ordinary Kriging provides a robust framework for capturing the spatial structure and correlation in the data, resulting in more accurate interpolations when spatial continuity is a significant factor.

B. Error Metric and Validation

The performance of each interpolation method was evaluated using the root mean square error (RMSE), a widely used metric that quantifies the average difference between predicted and actual soil moisture values. RMSE provides a single value that captures the magnitude of errors in the predictions, with lower values indicating closer alignment between the interpolated (predicted) values and the observed (measured) data. To provide a thorough evaluation of each method's accuracy, error comparisons were made both at individual timestamps and across the entire reference period. This dual approach allows for an in-depth analysis of performance at specific moments in time, as well as a broader assessment of how the models perform over a longer duration. By using RMSE in this way, the study ensures a comprehensive and detailed understanding of each method's effectiveness in predicting soil moisture accurately.

Then, in order to effectively validate the accuracy of the results and the generalizability of the interpolation models across various scenarios, three widely recognized validation approaches were employed: hold-out validation, k-fold cross-validation, and Leave-One-Out cross-validation (LOOCV). These methods help detect potential biases and variances in the model predictions, ultimately enhancing the robustness of the interpolation results.
Briefly, hold-out validation involves splitting the dataset into training and testing sets, providing an initial assessment of model performance on unobserved data. However, due to the limited number of data points at each timestamp, this method can exhibit high variability in the results, which may not provide a consistent measure of model performance. K-fold cross-validation addresses this variability by dividing the data into k equal parts. The model is trained on $k-1$ parts, tested on the remaining one, and iteratively repeated for all combinations. This approach leverages the entire dataset for training and validation, providing more stable and reliable results compared to hold-out validation. It ensures that each data point gets a chance to be in the training and the testing set, which improves the robustness of the validation process. LOOCV, a special case of k-fold cross-validation where $k = n$ (n is the total number of observations), iteratively leaves out one data point at a time for validation and train the model on the remaining points. This method offers less biased (but with greater variability) estimates and maximizes the use of available information, although it is computationally more intensive due to the large number of iterations required. This validation technique ensures that the model's predictive performance is tested against each individual data point, providing a thorough assessment of the interpolation accuracy.

C. Statistical Analysis

To determine whether the differences in RMSEs between the tested methods were statistically significant across the n timestamps considered, the respective error distributions were subjected to statistical validation. The analysis aimed to use a parametric statistical test, which requires the assumption of normality in the data distribution to produce consistent results. To verify this assumption, the Shapiro-Wilk (S-W) test was applied to assess the normality of the error differences. This test was performed on a small random sample of observations from each distribution, as it is particularly well-suited for small to medium-sized samples. In this case, the Shapiro-Wilk test maintains a good balance of accuracy and statistical power, effectively evaluating the normality of the data distribution. In detail, the Shapiro-Wilk test statistic W is defined as:

$$W = \frac{\left(\sum_{i=1}^{n} a_i d_{(i)}\right)^2}{\sum_{i=1}^{n} (d_{(i)} - \bar{d})^2} \tag{4}$$

where $d_{(i)}$ is the i-th order statistic (*i.e.*, the between values of two methods at the i-th timestamp), $\overline{d}$ is the mean of the differences between values of two methods across timestamps, and a_i are the coefficients calculated based on the expected values of $d_{(i)}$ from a standard normal distribution.

Therefore, (4) represents the ratio of the weighted sum of the ordered sample values to the sum of the squared differences between the sample values and their mean. The Shapiro-Wilk test statistic ranges from 0 to 1, with a W value close to 1 indicating that the sample is likely drawn from a normal distribution. For completeness, the normality of the data distribution was also checked using the Kolmogorov-Smirnov (K-S) test on the entire sample.
If the normality assumption was confirmed, a classical paired t-test was employed to determine the statistical significance of the differences over the entire period. The test statistic related to the paired t-test is defined as:

$$t = \frac{\overline{d}}{s_d/\sqrt{n}} \tag{5}$$

where $\overline{d}$ is the mean and s_d the standard deviation of the differences between values of two methods across timestamps.

Under the null hypothesis which assumes no difference between values across timestamps, the t-statistic follows a t-distribution with $n-1$ degrees of freedom [12]. These tests were crucial in confirming whether one interpolation method outperformed the other in accurately estimating soil moisture levels across the spatial domain considered.

IV. Analysis and Results

The analysis was conducted on a local machine using Python version 3.10, chosen for its popularity in the scientific community, extensive library support, and ease of customization. Custom functions were developed from scratch for specific tasks, while dedicated libraries facilitated other operations. NumPy and Pandas were used for efficient numerical computations and structured data manipulation, while the SciPy, IDW, and PyKrige libraries were employed to perform spatial interpolation tasks. The KD-Tree algorithm was frequently utilized for distance calculations, and several computations were optimized through parallel processing, improving overall efficiency and reducing execution times.

The results compare the performance of IDW and OK interpolation methods in estimating soil moisture across the study area. The analysis was initially carried out by focusing on specific times of a day in order to create interpolation maps. An example of an interpolation map is presented in Fig. 3, showing a heatmap of tensiometric soil levels generated using the IDW method on July 15, 2023, at midnight.

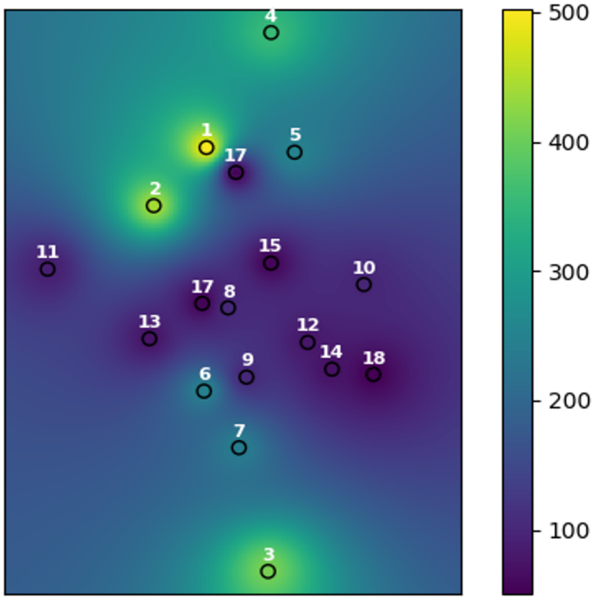

Fig. 3. Interpolation map built with IDW on July 15, 2023 at midnight

At a general level, considering the entire dataset, IDW has shown promising results in providing spatially distributed estimates. However, this technique tends to smooth variations, especially in areas with sparse sensor coverage. In contrast, a sensitivity analysis was conducted for OK to evaluate the impact of variogram parameters on the interpolation, selecting the exponential model as the best fit due to moderate spatial dependence. In fact, the empirical variogram closely matched the theoretical variogram of the exponential model. Other models displayed for the variogram were the spherical and Gaussian models, which seemed to fit the observed data slightly worse. These specific analyses are not included in this article due to space limitations. At the end, OK also demonstrated competitive performance.

The summary graph in Fig. 4 shows the average daily RMSEs of the time series for the two methods. The respective mean RMSE values were obtained using Holdout Validation, with the dataset split into 80% for training and 20% for testing at each timestamp. Based on the daily aggregated average values, there is slight visual evidence favoring the IDW method. The preference for a method seems to depend on the time period considered: IDW consistently performs slightly better than OK during the initial and final periods, while both methods produce nearly equivalent results in the central period.

Therefore, a quantitative validation campaign was conducted to select the best interpolation model for the dataset. More in detail, the validation techniques set out in the section III-A were applied. Specifically, 80-20 Holdout Validation,

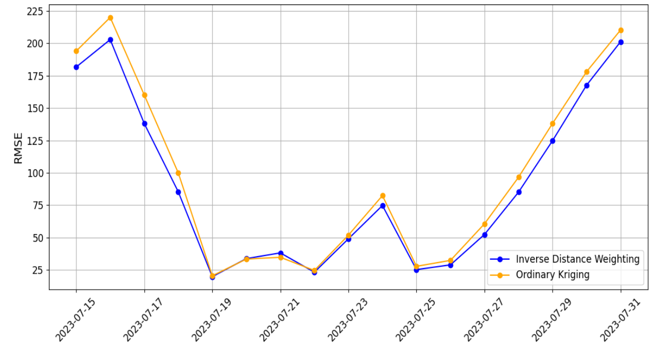

Fig. 4. Comparison of average RMSE values of IDW and OK over time

k-fold cross-validation with $k = 6$ (to ensure an integer fold division among the 18 tensiometers) and LOOCV were utilized. The validation techniques, including the fold division, were applied individually to each timestamp. Consequently, the distributions of RMSE values were analyzed over the entire reference period. To this end, Fig. 5 presents boxplots of the RMSE error distributions across timestamps for the two methods, categorized by the validation technique used.

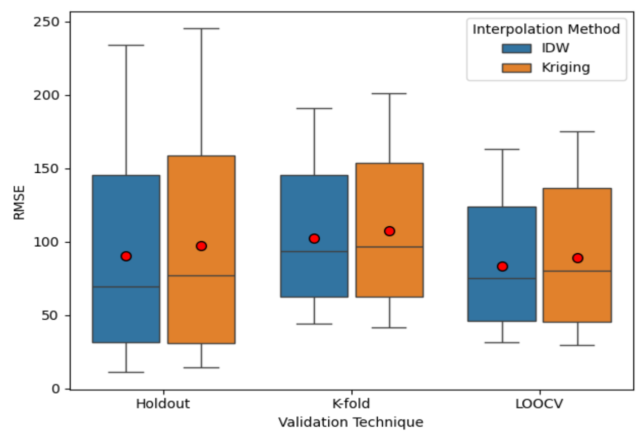

Fig. 5. Comparison of RMSE distributions for IDW and OK across various Validation Techniques

Observing the boxplots, the methods show very similar results, with IDW appearing to perform better than OK across all validation techniques. In fact, the mean, quartiles, and extremes of the RMSE distribution for the IDW method are consistently lower across all validation techniques compared to those of the OK method. However, since these differences are minimal relative to the reference scale, it is crucial to determine whether they are statistically significant.

A comprehensive statistical analysis was performed on the differences $RMSE_{IDW} - RMSE_{OK}$ to validate the results, with a 5% significance level as the threshold for reliable assessment. The assumption of normality in the RMSE differences between the two interpolation methods across timestamps was first tested using the Shapiro-Wilk test on a random sample of 50 observations, and the Kolmogorov-Smirnov test on the full dataset. This analysis was conducted for each validation method. The Shapiro-Wilk test consistently failed to reject the null hypothesis of normality for the differences, while the Kolmogorov-Smirnov test rejected normality except for the k-fold cross-validation method. Given that k-fold cross-validation is generally considered the most balanced validation technique, and the K-S test is highly sensitive to minor distribution deviations, it was reasonable to assume normality in the RMSE differences.

Consequently, a paired t-test was applied, yielding highly negative values and significant p-values across all validation methods. This indicates that RMSEs are consistently lower for the IDW method and that the differences are statistically significant. The analysis, therefore, demonstrates the superiority of IDW over OK for soil moisture estimation in the study area. Key distribution values for the methods, along with corresponding statistical test results, are presented in Table II.

TABLE II
RMSE COMPARISON OF INTERPOLATION METHODS

Validation		**IDW**	**OK**	**IDW - OK**
Holdout	mean	90.13	97.43	-7.30
	median	69.18	76.83	-7.65
	std	67.04	71.58	
	S-W (p-value)			0.96 (0.088)
	K-S (p-value)			0.08 (0.015)
	t-test (p-value)			-17.92 ($\approx$ 0)
K-fold	mean	102.60	107.28	-4.68
	median	93.50	96.77	-3.27
	std	43.46	46.68	
	S-W (p-value)			0.96 (0.074)
	K-S (p-value)			0.06 (0.118)
	t-test (p-value)			-9.88 ($\approx$ 0)
LOOCV	mean	83.58	89.06	-5.48
	median	75.04	80.08	-5.04
	std	40.58	44.07	
	S-W (p-value)			0.97 (0.208)
	K-S (p-value)			0.08 (0.012)
	t-test (p-value)			-11.49 ($\approx$ 0)

Lastly, it is important to note that OK was found to have a higher computational cost compared to IDW. This is particularly relevant for large-scale applications, where computational efficiency is a key consideration. The inferior performance of OK is likely attributed to the relatively low number of sampled points, making it less suitable for datasets with limited spatial coverage. However, OK remains a viable method when more tensiometers or additional sensors are deployed.

V. CONCLUSION AND FUTURE WORKS

This study highlights the pivotal role of interpolation techniques in optimizing irrigation schedules and improving agricultural productivity through accurate soil moisture estimation. Among the techniques evaluated, Inverse Distance Weighting (IDW) demonstrated superior performance in capturing local soil moisture variability within the Tres region of Trentino. Its simplicity and effectiveness in producing spatially distributed estimates make IDW a practical choice for real-time agricultural management in similar contexts.
However, it is essential to acknowledge the limitations of this study. The findings are based on a specific geographic area, where sensor distribution and environmental conditions may influence interpolation outcomes. In areas with sparse sensor coverage, IDW tended to smooth variations, potentially affecting its applicability in more complex agricultural landscapes. Additionally, significant variability can occur between closely spaced points due to differences in irrigation timing, underscoring the need for methods that account for this factor. Looking forward, future research could explore hybrid approaches that integrate machine learning algorithms or advanced geostatistical models, such as co-Kriging, that include other correlated variables related to soil moisture. These approaches could potentially enhance interpolation accuracy across diverse agricultural settings by better capturing complex spatial relationships and environmental factors.
Moreover, scalability studies are needed to assess the applicability of these techniques in larger agricultural regions where data density and variability present significant challenges.

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