



PADOVA, ITALY / OCTOBER 29-31, 2024

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

**IRRITRE: geographical information system for precision irrigation in Trentino**

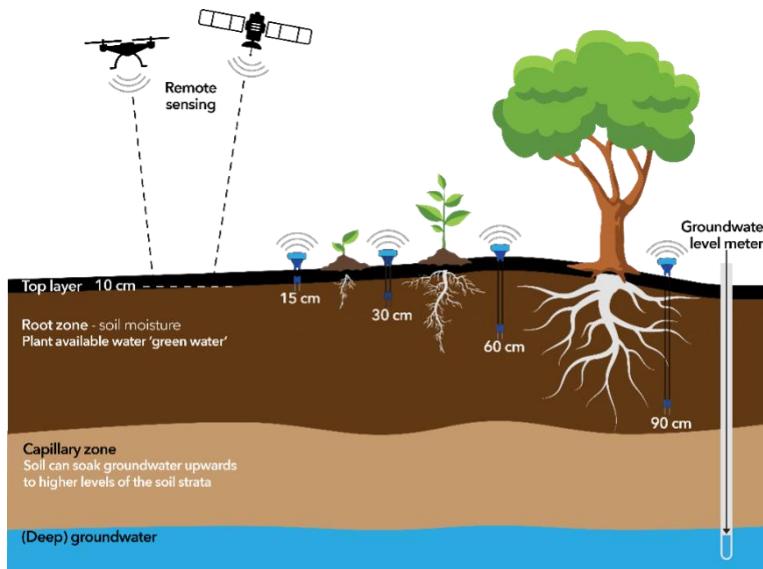
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# Introduction

## The Importance of Soil Moisture



- Efficient monitoring and management of **soil moisture** are essential for determining optimal irrigation schedules, reducing water waste, and promoting plant health
- In precision agriculture soil moisture is measured by a **network of tensiometers** deployed in the fields
- Remote and IoT sensors can be combined to provide **intelligent decision support systems** for farmers

Figure: Diagram showing Remote and IoT sensors measuring field characteristics

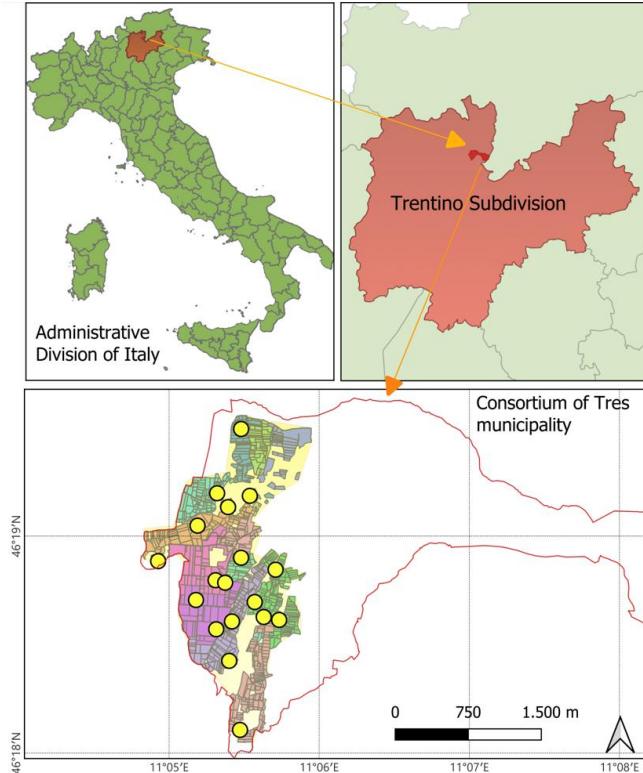
## Introduction

### Why Soil Moisture Interpolation?

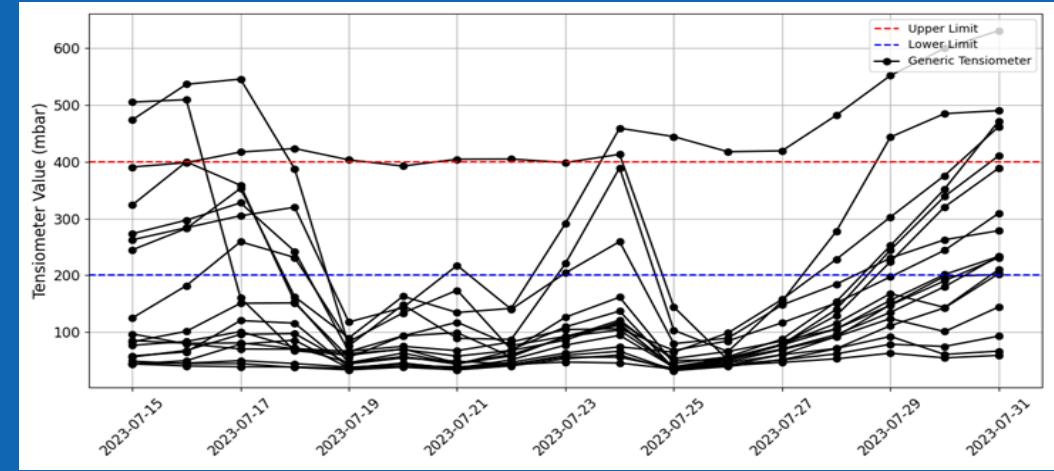
*" Spatial interpolation of soil moisture is essential for transforming point-based measurements into continuous maps, enabling comprehensive analysis across large agricultural areas "*

# Study Overview

## Dataset



**Figure:** Map showing the geographical area of the Tres consortium, where the tensiometers are installed



**Location:** Tres consortium of Trentino, Italy

**Period:** July 15 to July 31, 2023

**Data:** collected from 18 tensiometers, installed at depth of 30 centimeters, with measurements taken every 15 minutes

# Study Overview

## Research Objectives



### Applicability

Apply spatial interpolation methods to create maps for specific moments



### Comparison

Evaluate the performance of the methods using a reliable and consistent methodology



### Validation

Statistically assess whether the differences between methods are significant

# Methodology

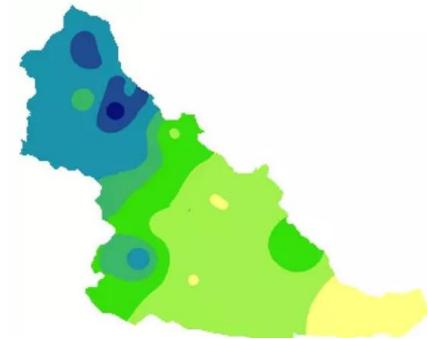
## Interpolation Methods

### Inverse Distance Weighting (IDW)

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

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.

Example Map:

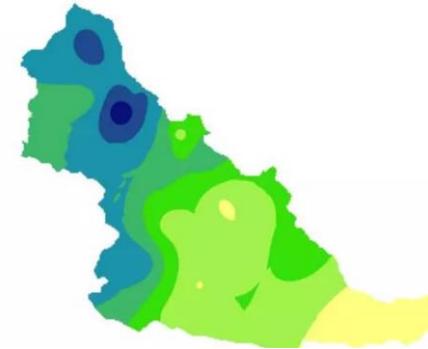


### Ordinary Kriging (OK)

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

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

Example Map:



# Methodology

## How to evaluate?

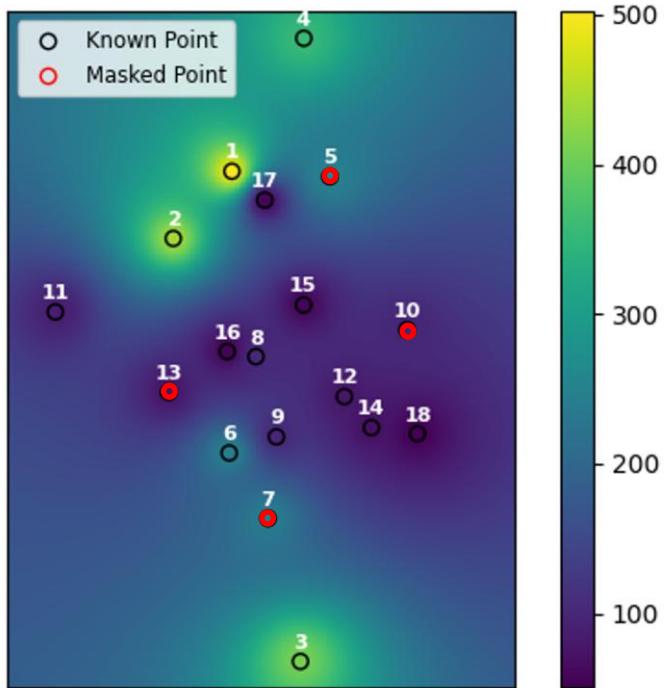


Figure: Interpolation map built with IDW on July 15, 2023 at midnight

- The data points need to be split into known and unknown categories to accurately evaluate estimation error and ensure reliable results
- RMSE serves as the primary evaluation metric because it effectively captures the differences between estimated and observed values
- Validation techniques and statistical methods are essential for validating the robustness of the results and preventing overfitting

# Results

## First Comparison

Graphical comparison of daily average RMSE values between IDW and OK interpolation methods, calculated using an 80-20 holdout validation:

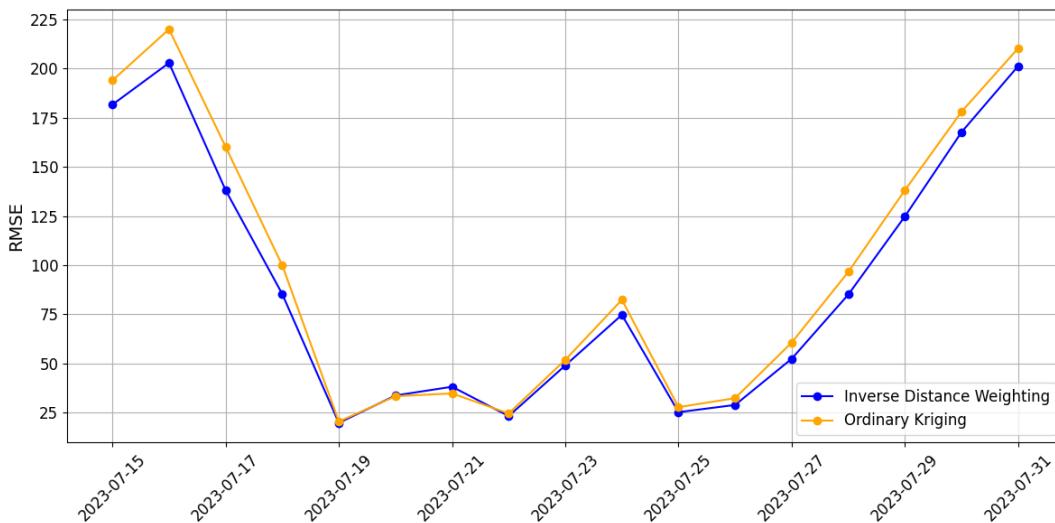


Figure: Comparison of average RMSE values of Inverse Distance Weighting and Ordinary Kriging over time

- **RMSE values show significant variation depending on the time period**
- **IDW slightly outperforms OK in certain periods, with near-equivalent performance in others**
- **Results are highly dependent on the validation method (which points are used for interpolation)**

## Results

### Cross-Validation Results

Graphical cross-validated comparison of RMSE values between IDW and OK interpolation methods:

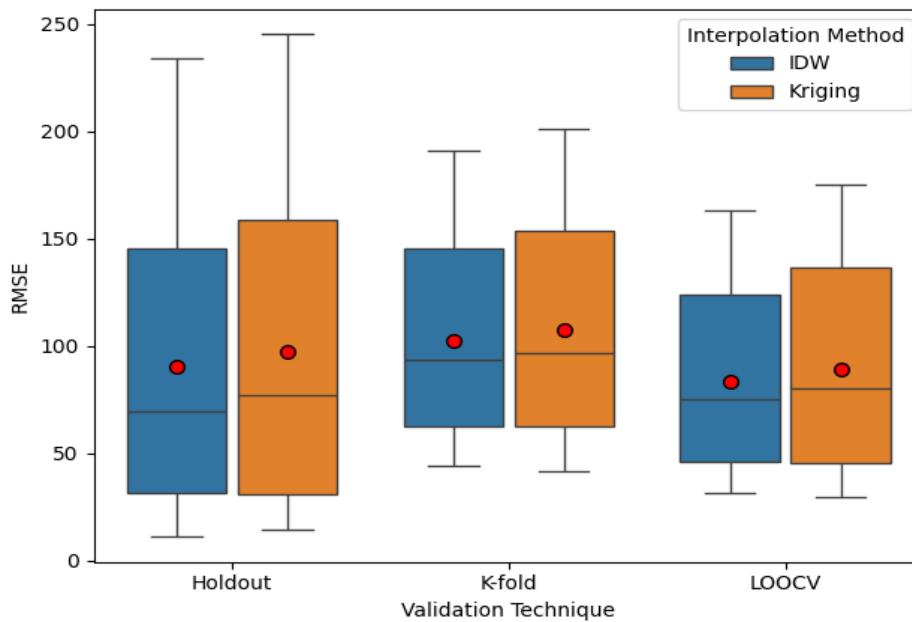


Figure: Comparison of RMSE distributions for Inverse Distance Weighting and Ordinary Kriging across various Validation Techniques

|         | IDW    | OK     | IDW – OK |
|---------|--------|--------|----------|
| Holdout | 90,13  | 97,43  | -7,30    |
| K-Fold  | 102,60 | 107,28 | -4,68    |
| LOOCV   | 83,58  | 89,06  | -5,48    |

- **IDW consistently outperforms OK across all validation techniques**
- **The differences between the two methods are minimal, raising questions about their statistical significance**

# Results

## Statistical Analysis

### 01 Compute the Differences

Calculate the RMSE differences between IDW and OK across all timestamps

### 02 Verify Assumptions

Use Kolmogorov-Smirnov test to check the normality assumption of the RMSE differences distribution

### 03 Apply Paired t-Test

Conduct a paired t-test to assess the statistical significance of the observed differences

|         | K-S Test<br>( <i>p</i> -value) | Paired t-Test<br>( <i>p</i> -value) | Result |
|---------|--------------------------------|-------------------------------------|--------|
| Holdout | 0.96 (0.088)                   | -17.92 ( $\approx 0$ )              | ✓      |
| K-Fold  | 0.96 (0.074)                   | -9.88 ( $\approx 0$ )               | ✓      |
| LOOCV   | 0.97 (0.208)                   | -11.49 ( $\approx 0$ )              | ✓      |

- **With a 5% significance level (*p*-value  $< 0.05$ ), the K-S test slightly fails to reject the null hypothesis, indicating that the assumption of normal distribution is satisfied**
- **Conversely, the paired t-test consistently rejects the null hypothesis, demonstrating that the RMSE differences are statistically significant**

# Conclusion

## Key Takeaways

01

In this study, IDW outperforms OK for soil moisture estimation. IDW is effective with sparse sensor data, whereas OK relies on a denser network to fully leverage spatial correlations.

Performance

02

IDW's simplicity and low computational cost make it a practical solution for real-time irrigation management under current field conditions. The error results are relatively small, given the context of the actual case study.

Applicability

03

The performance may vary with different datasets or larger sensor networks. These results are specific to this region and sensor setup, and IDW's smoothing of spatial variations could limit its accuracy in more complex environments.

Limitations

# Conclusion

## Future Directions



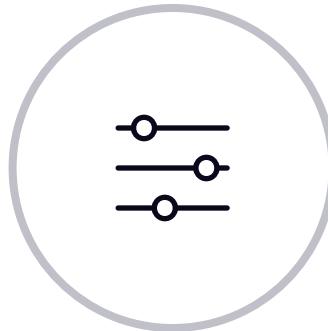
### Sensors

Expand the sensor network density to maximize the potential of both methods and improve spatial resolution



### Variables

Integrate other correlated factors, such as irrigations, to enhance the accuracy and relevance of the analysis



### Methods

Evaluate other interpolation techniques (splines, co-kriging, deep learning) to identify potential improvements



### Scalability

Investigate how the methods perform in other regions to evaluate the scalability and to diverse conditions

thank you