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Spatio-temporal decision uncertainty of selected soil physical parameters can enhance variable rate irrigation

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Abstract: The effectiveness of crop irrigation via sprinkler systems could be improved by environmental variability inherent to field conditions, thus leading to the sub-optimal irrigation of certain sections. To rectify this discrepancy, in-situ soil characteristics were methodically correlated with the region's hydrological circumstances and root zone, assigning a distinct level of uncertainty to each decision point. A stochastic geodatabase was then generated, offering prospective applications in precision agriculture. The experimental agricultural field in Nyírbátor, Hungary, served as the reference point, with the constraints posed by variability being surmounted through a dual-layer iteration of random sampling structures employing the sequential Gaussian simulation (SGS) method. For this purpose, 25 physical, 9 chemical, and 11 soil microelements were examined from samples extracted from 105 boreholes in an 85-hectare cornfield while adopting a regular sampling scheme within a 100 x 100 m grid. Each soil parameter estimation underwent the following process: 1. Organization of data and application of exploratory statistics for outlier identification; 2. Normal score transformation; 3. Exploratory variography; 4. Sequential Gaussian simulations, leading to the construction of a series of plausible, equally probable realizations; 5. Computation of medians and the 95% confidence intervals. These methodologies were deployed concerning the soil characteristics, with porosity being selected as the representative soil parameter for the Nyírbátor cornfield. Porosity was our focus physical parameter because the micro and macro soil structures greatly influence the hydraulic characteristics of the soil such as water infiltration, hydraulic conductivity and moisture retention. Comparative assessments of the Hydrus 3D hydrological models of kriged and sequential Gaussian simulation surfaces were conducted. Results highlighted the efficacy of sequential Gaussian simulation in encapsulating the field's heterogeneity, and the accompanying uncertainty served as a decision-making tool in the diversified water application across the field. The results were validated using field data observations of soil moisture in the corn field from 2020 and 2021 respectively and nonetheless, the uncertainty divergence between the Hydrus outputs unveiled the knowledge deficit concerning actual spatial patterns of soil porosity. The established workflow offers a cost-efficient dynamic methodology for water resource management, potentially curtailing overall irrigation expenditure by variably applying water to parcels based on uncertainty estimates.

Keywords: Spatio-temporal decision uncertainty, Sequential Gaussian simulation, cost-effective irrigation

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Introduction

Water application through irrigation enhances crop productivity and contributes significantly to the water balance of agricultural fields. One of the most significant limitations that reduces the efficiency of water applicators such as sprinkler heads is the presence of field variability that leads to some subareas being over or under-irrigated. Temporal variability in this context is caused by the type of irrigation device used, Spatial variability is attributed to the type of crop grown and soil in the farming unit, making it challenging to schedule uniform water distribution. The varying magnitudes of the existing physical properties create uncertainties across the entire agricultural fields and thus managing water resources in precision farming is paramount, for the right amount of water at the targeted spot and time. Several strategies of irrigation based on soil moisture balance modelling and soil moisture content sensing have been greatly used in scheduling variable rate irrigation to improve water use efficiencies (Li et al., 2018; Sui et al., 2015), as well as enabling the monitoring of water fluctuations within the soil profile (Zhao et al., 2018). Current soil water balance methods heavily rely on meteorological weather station data to forecast available soil moisture, making them cheaper and are highly preferred and used methods in precision irrigation (Sui & Vories, 2020). Other physical models in relation to sprinkler applicators focus on improving water distribution patterns, based on shape and nozzle size to improve applicator efficiencies (Borges Júnior & Andrade, 2021; Hua et al., 2022). The use of various static and real- time datasets in precise water applications can contribute to the efficiency of agricultural decisions, with several model-based irrigation methods being used for scheduling irrigation (Bwambale et al., 2023).

Soil physical and chemical properties are among the factors greatly attributed to spatial field variabilities, hindering the successful automation of water application by irrigation applicators. However certain soil properties possess specific spatial autocorrelations with a distribution over space whose heterogeneity can be estimated (Nyengere et al., 2023). Investigating spatial patterns for the soil parameters is vital in modeling environmental processes and sustainable agricultural production regarding specific soil and water management (Quigley et al., 2018), but our limited ability to observe environmental parameters requires incorporating a specific degree of uncertainty for each decision to be completed (Bi et al., 2023). Since our possibility to observe nature entirely is impossible, the observations can be considered representative only to a limited extent and beyond this extent, every determined value is just an assumption. This assumption is established using optimal spatial estimates, such as some interpolated surfaces of the input parameter. The spatial estimation of specific soil properties, such as porosity, can be vital for identifying field parcels that require greater attention and management. Soil porosity plays a pivotal role in water conduction, air circulation and as such, directly influences the hydraulic characteristics of soil such as moisture retention, infiltration, and hydraulic conductivity (Indoria et al., 2017).

Applying geostatistical techniques can be useful in predicting and interpreting the variables of given parameters at unsampled points, whose map outputs can then be used for decision-making (Faechner et al., 2000). The most applied complex environmental and numerical models typically ignore the input dataset's uncertainty; instead, they have a built-in function. These interpolation techniques consider spatial correlations between observed values as of great importance in predicting values at unsampled points (exact interpolators), and as such, small values are overestimated and large values are under-estimated due to the ignorance of the estimated statistics of the values (Deutsch & Journel, 1992). This reduces the certainty for concrete decision-making due to the blurred variability and spatial patterns generated by these models.

These limitations in this study are overcome using a two-level iteration of randomized sampling structures using the sequential Gaussian simulation to reproduce the sample value statistics and show the spatial continuity of the data (Deutsch & Jour-

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nel, 1992; Rossi et al., 1993). Our project uses a stochastic modeling approach to estimate the uncertainty of selected soil parameters over space. The uncertainty meant assuming measured values of soil parameters to differ from reality (actual realizations). Specifically, the study aimed at (i) analyzing the spatial variability of selected soil physical properties that directly affect soil water retention on a commercial agricultural field, and (ii) improve automatized irrigation efficiency through site specific interventions based on uncertainty. As an example to demonstrate the cruciality of uncertainty in irrigation, this study based on the model of soil moisture and water fluxes in a maize field to further improve the optimization of irrigation (Magyar et al., 2023).

Materials and Methods

The experimental study area

The experimental field is situated in the alluvial cone plains of the North-Western part of Hungary (Fig 1). Sandy loam soils are the dominant soil type, with corn grown extensively for dairy feeding. Along the middle field, boundaries are delineated by asphalt roads, with an irrigation channel filled with treated wastewater from the animal farms. The groundwater table is about 2.5 m deep, and the horizontal fragmentation of the landscape is low due to melioration and drainage activities performed in the previous century. On the hottest summer days, the maximum temperature can exceed 34 °C, and about 350–360 mm of rainfall is received in the summer half of the year. The region's climate suits slightly heat-sensitive and water-intensive agricultural crop production. Thus, a Reinke 2060 PL sprinkler linear irrigation system is installed to supplement water requirements to crops during water scarcity periods as recommended by Tamás et al. (2018) within the WATERAGRI project framework.

Data Collection

Spatially referenced data, such as soil field perimeters, were meticulously extracted using ArcGIS Pro software, a highly advanced and widely utilized geospatial processing program. Coordinates were determined using real time kinematic global positioning system (RTK-GPS), which offers centimeter-level precision in positioning, significantly enhancing the accuracy of data collection (Sun et al., 2010).

Soil samples were procured from 105 designated locations across an extensive 85-hectare irrigated maize field. This sampling was performed at two distinct strata, precisely at 30 cm and 60 cm depths, adhering to a systematic sampling design arranged in a 100 m-by-100 m grid (Fig 1). This regular grid-based sampling was employed to ensure homogeneity in the data collection process, thereby minimizing the introduction of sampling bias and allowing a representative understanding of the spatial variability within the field. Furthermore, the selected grid size helped to obtain an optimal distribution and patterns of soil properties without losing significant information (Soulis, 2013). In each location, soil samples were collected from five distinct soil horizons, delineated by depth: 0–20 cm, 20–40 cm, 40–60 cm, 60–80 cm, and 80–100 cm and analyzed for their respective physical and chemical properties. This stratified approach to sampling ensured comprehensive coverage of the soil profile, allowing for the elucidation of patterns and trends in soil properties across different depths, each of which may exert different influences on water and nutrient dynamics and, consequently, on crop productivity.

The array of the geodatabase associated with the experimental field encompassed a broad range of the soil's physical and chemical parameters as depicted in Fig 2. These parameters offered valuable insights into the inherent and derived properties of the soil, influencing critical factors such as water holding capacity, nutrient availability, and soil

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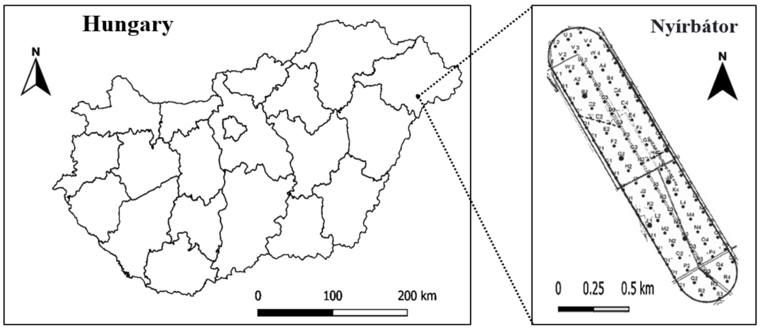

Figure 1: Map showing the location of the experimental site in Nyírbátor, Hungary.

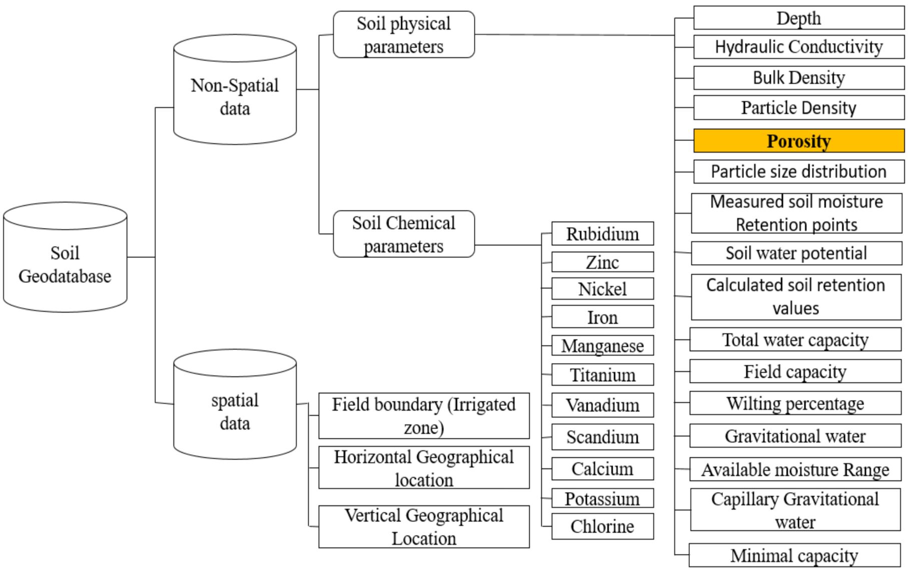

Figure 2: Geodatabase of the Nyírbátor cornfield.

structure, all of which are critical determinants of crop growth and productivity. The extensive geodatabase, a comprehensive and integrated repository of geographically referenced data, was constructed incorporating these crucial soil parameters. This incorporation was achieved via a systematic collation and assimilation process, ensuring accurate alignment of the non-spatial data with the corresponding spatial data. The geodatabase was seamlessly integrated into the Geographic Information System (GIS) project, a powerful toolset for manipulating, analyzing, and displaying geospatial data. Integrating the geodatabase within the GIS environment facilitated an efficient framework for storing and retrieving diverse soil-related data (Kabolizadeh et al., 2023). This framework provided a robust platform for the rigorous analysis of these multi-dimensional datasets, enabling extracting meaningful patterns, relationships, and trends. Furthermore, it served as a sophisticated tool for interpreting the data, allowing the translation of raw data into actionable information and knowledge. This dynamic amalgamation of non-spatial data into a GIS project allows for a more comprehensive and granular understanding of the complex interactions and relationships between various soil properties and their influence on agricultural practices and outcomes.

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Sequential Gaussian simulation

This manuscript has an abridged exposition of the employed model features, with Deutsch and Journel (1992) and Goovaerts (1997) providing more expansive elucidations. For this investigation, point source soil data were enlisted, and soil porosity was selected as the demonstration variable, denoted as P at disparate locations symbolized as y.

The key to successful irrigation nests on having an in-depth knowledge of the micro and macro soil structure as this greatly influences the movement of water in the soil. Topsoil for many soil types is usually unsaturated and thus an investigation of its voidness is usually vital for water management and assessing the hydraulic behaviors within the soil (Wang et al., 2023).

The multivariate distribution of $P(y)$ at a specified count (n) of locales is articulated as $y1, y2, y3...yn$ and can be represented via the function:

$$[f(y1\ldots,yn;p1,\ldots,pn)] \tag{1}$$

Equation (1) can subsequently be expanded into the product of its location-specific (n) univariate conditional distributions:

$$f(y1,\ldots,yn;p1,\ldots,pn) = f(y1;p1)xf(y2;p2| \\ P(y1)=p1)x\ldots f(yn;pn| \\ P(yt)=Pt, t=1,\ldots,n-1) \tag{2}$$

For instance, the probability distribution of porosity at the second location, $P(y2)$, assuming the porosity value at the first location $P(y1)$ to be $p1$, is depicted as $f(y2;p2P(y1)=p1)$. A random sequence of the prior univariate conditions generates a realization of $P(y)$, indicated as $p(y)$, thus establishing novel conditions for the porosity samples. The algorithm uses the distribution $f(y1;p1)$ to randomly select a realization, $y1$, to represent $P(y1)$. This process is iteratively executed until the final distribution, $f(yn;pnP(yt)=Pt, t=1\ldots,n-1)$, is conditioned, with the final realization, pn, randomly extracted from the conditional distribution.

The execution of the sequential Gaussian algorithm was achieved by adhering to the following procedural steps (Deutsch & Journel, 1992):

1. The initial dataset representing soil porosity was subjected to a normal score transformation. This step, a form of data standardization, aimed to convert the original, irregularly distributed porosity data into a normalized dataset, consequently facilitating subsequent stages of analysis.
2. Subsequently, a grid was superimposed onto the transformed data points. This grid establishment step acted as a preparatory phase for the spatial analysis, providing a structured format that enabled the accurate and precise localization of data points.
3. Grid nodes, marking the intersections of grid lines, were systematically identified, and subjected to a simple kriging estimation procedure. Simple kriging is a geostatistical method, leveraged spatial autocorrelation within the data to provide an unbiased estimation of values at unsampled grid nodes.
4. The local probability distribution at each node was defined by utilizing the expected values and the kriging variances. This step allowed the assignment of a distribution to each grid node, providing a probabilistic understanding of the soil porosity at each location.
5. The algorithm then randomly selected values from these defined probability distributions to be assigned as the grid node values. This stochastic process ensured that the assigned values appropriately reflected the inherent variability and uncertainty within the dataset.
6. The entire procedure was iteratively

carried out for all the grid nodes. This exhaustive approach ensured that the complete spatial extent of the field was covered, producing a comprehensive spatial representation of soil porosity.

After completing these steps, multiple equally probable spatial distributions of porosity $P(y)$ were generated. These distributions, also known as stochastic images or realizations, represented varying potential states of soil porosity across the field, reflecting this soil property's inherent spatial variability and uncertainty (Fig 3).

Results and discussion

The inaugural step in the data analysis process was ascertaining the vertical distribution and the associated probability of porosity data throughout the soil profile (Fig 4). The process aimed to comprehend the changes in porosity values with increasing depth, thereby providing a vertical profile of soil porosity. An assessment of median porosity values at the 60 cm depth reveals a symmetrical distribution pattern (Fig 4b). This symmetrical dispersion signifies a central tendency in the dataset, where the bulk of the data points clusters around the median, demonstrating the relatively homogeneous nature of soil porosity at this depth.

Further scrutiny reveals the mean porosity value at 30 cm depth to be approximately 38.46%, while the same at 60 cm is marginally lower at 38.3%. A detailed examination of these values and the corresponding graphs insinuates a high probability that most porosity values cluster around 38.3% at the 60 cm depth. This indication of a potential central tendency reinforces the understanding of soil porosity distribution at this depth. Additionally, the insignificant standard deviation associated with the porosity values at the 60 cm depth suggests a high degree of consistency within the dataset. This implies that 95% of the porosity values are expected to lie within the $38.3 \pm 2.9\%$ range. This calculated range encapsulates the spread of porosity values around the mean, thereby providing a measure of the data variability and offering further insights into the overall uncertainty of the soil porosity distribution.

The spatial continuity of soil porosity was examined by applying semi variograms, which were utilized to visually represent the variation of the soil parameter across the spatial extent of the field (Fig 5). This geostatistical analysis method facilitated identifying trends in spatial continuity in specific orientations.

A substantial degree of spatial continuity in soil porosity was discerned, extending in the northeastern and northwestern direction of the field at 60cm and 30 cm depth respectively. Conversely, a markedly smaller degree of continuity was detected in the southwestern direction at 60 cm and at 30 cm depth stretching from west to the eastern direction of the field. These distinct patterns of spatial continuity reflect the impact of anthropogenic factors that have influenced soil characteristics and the resultant spatial distribution of higher porosity values throughout the field. In areas exhibiting high soil porosity, it was inferred that the water demand would likely be elevated due to highly porous soils' reduced moisture retention capacity. This information provides invaluable insights for effectively managing water resources during irrigation. Specifically, it allows for identifying areas necessitating more frequent or higher volumes of water application, facilitating a targeted approach in irrigation management that accommodates the spatial variability in soil porosity.

Figure 6 presents a spatial autocorrelation analysis of the simulated porosity values. The x-axis of this figure represents the distance separating individual sample points. At the same time, the y-axis denotes the semi variance, a metric quantifying the degree of

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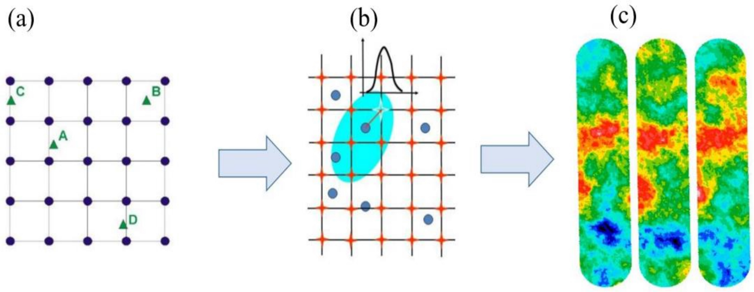

Figure 3: Simulation Workflow: Grid nodes and sample points (a); the local probability distributions at each node (b) and the Resultant 100 Equally Probable Realizations (c).

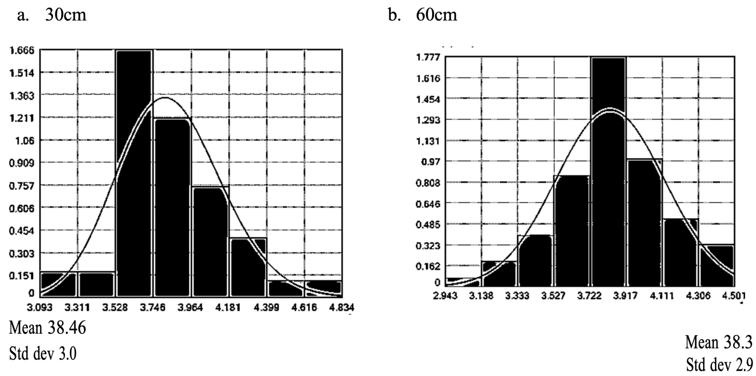

Figure 4: Porosity realizations at 30 cm and 60 cm depth.

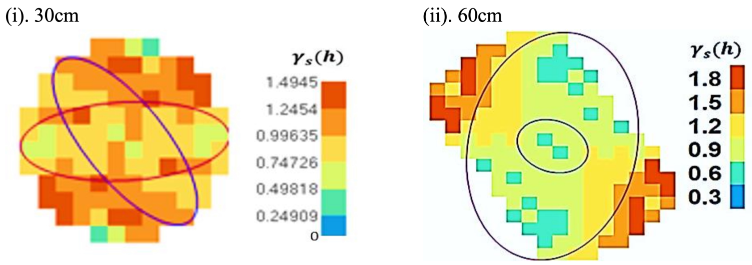

Figure 5: Semi variogram map showing spatial continuity of soil porosity at 30 cm and 60 cm depth.

spatial dependency between pairs of porosity samples. This analysis provides an additional layer of understanding regarding the spatial structure of soil porosity across the field, further contributing to the optimization of water management strategies.

In Figure 6. (a) and (b) respectively, an examination of soil porosity at a lag distance of 240 m and 668.3 m reveals the cessation of spatial autocorrelation amongst soil porosity values. Correspondingly, there is a termination of the increase in semi variance observed at these distances. This cessation signifies that beyond these distances, the spatial

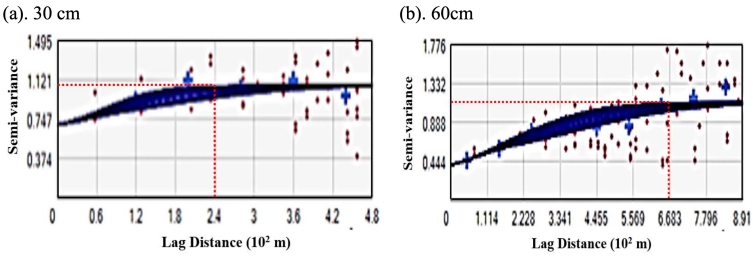

Figure 6: Spatial autocorrelation of soil porosity values at 30 cm and 60cm depth.

distribution of soil porosity values no longer exhibits the pattern of correlation previously observed closer to the surface. This pattern, characterized by a high degree of spatial autocorrelation amongst nearby points, signifies that the soil porosity values are more similar at shorter distances than at greater separations. Thus, observations positioned closer to each other exhibit a lower semi variance, indicating a higher correlation, as compared to the semi variance and correlation of more distantly positioned observations.

This trend, evidenced by the leveling of the semi variance, informs us that the spatial continuity of soil porosity observed at the shallower depth ceases at 240 m and 668.3 m distance within the agricultural field at 30 cm and 60 cm depth respectively. This critical observation can significantly inform water management strategies, particularly in determining the depth, distance and intervals at which irrigation is most effective, considering the variable porosity and spatial distribution.

Comparison of alternative porosity estimations

A comprehensive series of one hundred simulations for porosity values as well as other physical and chemical parameters within the constructed geodatabase were undertaken, encompassing an extensive spatial area of 850 m$\times$1000 m, equivalent to 85 Ha for all the variables. This simulation suite involved assigning values and normal scores to several nodes within the designated grid, each of which was subjected to an intricate simulation process. The grid node simulation was performed using the simple kriging interpolation method coupled with applying anisotropic semi variograms. This technique enabled the systematic calculation and projection of porosity data across the grid based on known data points, accounting for anisotropy or the directional dependence of spatial continuity.

Each of these simulated realizations possesses an equal probability of occurrence and a high degree of likelihood. As such, the mean of the values at each grid node from all simulations, termed E-type estimations (ensemble average mapping), was calculated to provide a comprehensive spatial representation of the porosity data and all other parameters (Fig 7). These E-type estimations are consolidated outcomes of the multiple probable simulations and provide a spatially averaged overview of soil porosity across the field. The resultant E-type estimations divulge the spatial configuration of the mean for all the 100 equiprobable simulations, offering a graphical representation on the maps. These maps provide invaluable insights into the spatial variation of soil porosity across the field, facilitating the implementation of site-specific farm management decisions (Faechner et al., 2000). This precise and comprehensive overview of spatial patterns can aid in optimizing irrigation strategies, considering the spatial variability of soil porosity.

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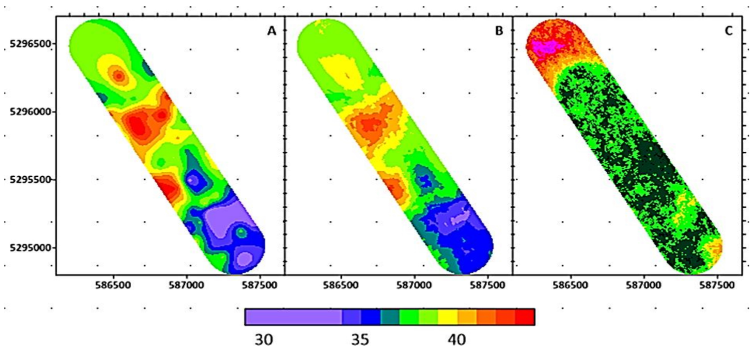

Figure 7: Estimation by Simple Kriging (A), The expected value of 100 stochastic images based on SGS (B), the width of the confidence interval for porosity Estimation (C).

Depicted in Figure 7 (a) and (b) are the representations of the Kriged and Sequential Gaussian Simulation (SGS) realizations, respectively, both demonstrating analogous spatial patterns due to low degrees of spatial interpolation. A prominent feature shared by both representations is the existence of high porosity values in the central areas of the field. This observation can be attributed to soil conditions characterized by larger particle size distributions, inherently leading to high soil porosity within these regions. Nevertheless, the model predicts moderate to low porosity values in other field regions, contingent upon the spatial distribution and proximity of specific soil physical parameters. Beyond the determined range, these porosity values are observed to be independent. Consequently, there are instances where higher values may be predicted while lower porosity values may be derived in other scenarios. Such fluctuations highlight the inherent variability in soil physical properties across the field. Moreover, Figure 7 (C) presents the confidence intervals of the simulated porosity values, effectively illustrating areas of heightened uncertainty. In regions lacking sufficient observational data, an increase in uncertainty is evident. This uncertainty stems from a dearth of information regarding the field's specific soil conditions, reinforcing the necessity of further soil sampling to mitigate these uncertainties and enhance the precision of soil porosity predictions.

Figure 8 exhibits the outcomes of 100 three-dimensional (3D) Hydrus estimations obtained using 100 distinct yet equiprobable porosity estimations as input grids. Discrepancies in the outputs of the Hydrus model highlight the impact of limited knowledge pertaining to the inherit spatial patterns of soil porosity. In the simple kriging approach, the average was taken outside the range of known values. Conversely, the sequential Gaussian simulation (SGS) algorithm aimed to preserve variations within the datasets, thus offering a more practical means of capturing uncertainties and variabilities in soil porosity.

SGS, as demonstrated in the results, showcased minimal heterogeneities within the field, effectively representing the spatial continuity of porosity following the corresponding locations. In contrast, the Kriging method underestimated larger porosity values while overestimating smaller ones. This disparity underscores the inherent limitations of kriging in accurately capturing the true magnitude and distribution of soil porosity. Using SGS allows for a more comprehensive depiction of the spatial variations and uncertainties in soil porosity. It provides valuable insights into the spatial connectivity and continuity of porosity across the field. In con-

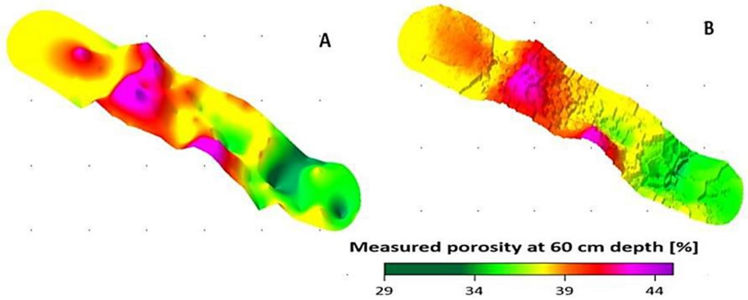

Figure 8: Comparison of the results of the kriged (A) and simulated surfaces(B).

trast, kriging falls short of capturing these essential aspects due to its inherent assumptions and limitations. These findings emphasize the significance of employing advanced modeling techniques like SGS, which offer a more robust and accurate representation of the spatial patterns and uncertainties in soil porosity. Such methods enable researchers and practitioners to make more informed decisions regarding soil management practices and water resource optimization in agricultural systems.

Comparison of the results to the Water balance of the Hydrus model

Figure 9 presents the outcomes of optimal soil moisture estimations using the Hydrus 2D model and sequential Gaussian simulation (SGS). The Hydrus 2D model was validated using field data observations of soil moisture in the corn field from 2020 and 2021 respectively. Notably, the simulated moisture content is closely aligned with the actual measured soil moisture content, indicating the efficacy of the modeling approaches (Magyar et al., 2023). The grey area in the figure represents the 95% confidence interval, with thicker areas indicating a higher degree of uncertainty in estimating soil water content (Karandish & Šimůnek, 2019). During the growth period of corn from May to August, a noticeable decline in soil moisture content was observed from planting to physiological maturity. This pattern aligns with established knowledge regarding the water requirements of corn crops, as water consumption increases during the active growth stages and diminishes towards maturity. The threshold porosity probability values derived from the simulations, particularly at 30 and 60 cm depths, are particularly informative during dry periods. These values hold the potential to reflect the specific water demands of the crops, considering the unique characteristics of the soil profile. Consequently, these estimations serve as valuable inputs for informed farm management decisions, aiding in optimizing irrigation strategies and resource allocation. By utilizing the simulation outputs and the generated threshold porosity probability values, practitioners and farmers can make data-driven decisions regarding irrigation scheduling, ensuring that water is applied judiciously and following the varying water demands of the crops throughout the growing season. This approach allows for more efficient water management, reducing unnecessary water usage and promoting sustainable agricultural practices.

Conclusion

Soil physical properties, especially porosity, play vital roles in the hydraulic behavior and distribution of water across the soil media. The knowledge of porosity variability within irrigated agricultural fields can help in the

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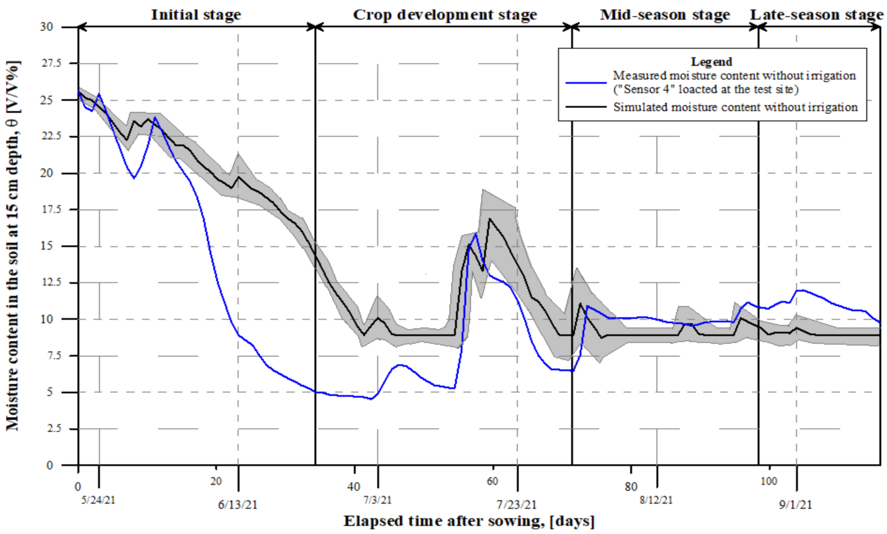

Figure 9: Measured and simulated soil moisture Contents for the Nyírbátor site in the vegetative period 2021 (Magyar et al., 2023).

development of effective water use strategies to minimize water wastages.

The spatial patterns generated by the sequential Gaussian simulation (SGS) were leveraged to delineate specific parcels within the cropland where soil porosity was projected to directly or indirectly impact water use and management. These simulations elucidated the uncertainty associated with soil parameters, specifically porosity, by revealing areas characterized by varying porosity, including high, low, and moderate values. The output that best represented the initial data was selected from the numerous realizations obtained from the simulations. This optimal output was determined by considering the general agreement with the observed data and the ability to capture the spatial variability and uncertainty in the porosity distribution.

The uncertainty analysis was conducted based on the confidence intervals derived from the expected porosity values. These confidence intervals provided a quantifiable measure of uncertainty, offering valuable insights for irrigation management decisions. By utilizing this uncertainty information, irrigation practices can be adjusted, with particular attention given to areas with porosity values below threshold limits or exceptionally high values. This approach enables a targeted and site-specific approach to irrigation management, focusing on areas where the soil porosity may pose challenges or opportunities for effective water use. Water resources can be utilized more efficiently by tailoring irrigation strategies to address the variability in porosity values, ensuring that water application aligns with the specific needs of different areas within the cropland. This proactive management approach contributes to sustainable water management practices, optimizing crop productivity while minimizing unnecessary water usage.

Recommendations

The physical and chemical nature of soil keeps on changing over time due to increased physical, chemical, and biological activities, altering the nature of soil. For high efficiency to be achieved during irrigation, we recommend an annual soil sampling, testing and simulations interval to keep in check of the continuous soil formation, physical and chemical alterations.

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