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INTRA-FIELD SPATIAL HETEROGENEITY PREDICTION FOR THE PURPOSES OF PRECISION FARMING: COMPARISON OF FREQUENCY RATIO AND SHANNON'S ENTROPY MODELS

Tamara MYSLYVA[1], Petro NADTOCHIY[2], Yurii BILYAVSKYI[3], Petro TROFYMENKO[4]

[1]Polytechnic College Suriname, Slangenhoutstraat, 99A, Paramaribo, Republic of Suriname
[2]Institute of Agriculture of Polissia NAAS of Ukraine, Kyiv highway, 132, 10132, Zhytomyr, Ukraine
[3]Zhytomyr Agricultural Technical Professional College, 96 Pokrovska Street, 10008, Zhytomyr, Ukraine
[4]Taras Shevchenko National University of Kyiv, 60 Volodymyrska Street, 01033, Kyiv, Ukraine

Corresponding author email: byrty41@yahoo.com

Abstract

This paper provides the results of assessing the possibility of using frequency ratio (FR) and Shannon's entropy (SE) models to predict the intra-field spatial heterogeneity zones (IFHZ) which are taken into account when performing various technological processes in precision farming. The studies were carried out in 2021-2022 in the Radomyshl community of Zhytomyr raion (Zhytomyr oblast, Ukraine) in an area of 6.602 km². To determine IFHZ, nine soil parameters were used, the suitability of which for prediction was determined by multicollinear analysis. These data include the hydrolytic acidity, nitrogen, phosphorus and potassium content, the soil buffer balance index, and B, Mo, Cu, and Zn content. The area under the receiver operating characteristic (AUROC) method has been utilised to validate both FR and SE models. The research suggests that the AUROC curve for SE (0.84) was better than that for FR (0.82). Hence, the SE model predicts IFHZ more accurately than the multivariate statistical model FR in the study area.

Key words*: intra-field heterogeneity, forecasting; frequency ratio, Shannon's entropy, model comparison.*

INTRODUCTION

Precision farming technology provides a viable solution for managing profitability and reducing production costs in agriculture, especially in the face of dwindling farmland and increasing energy and raw material costs for mineral fertilizers (Myslyva et al., 2021; Hrynevych et al., 2022). This assertion is supported by the expected growth of the precision farming market to $11.54 billion by 2026, with a CAGR of 14.3% (ReportLinker, 2022).

Ukraine is an important global agricultural producer, accounting for 41% of the country's total exports in 2021, and is a top exporter of sunflower meal and oil, corn, and wheat (USDA, 2022). Precision farming technology has already gained significant traction in Ukraine, with an average usage percentage of 51.2% (UCAB, 2021). Its relevance to the Ukrainian agrarian sector is particularly noteworthy, given the shift in the main grain production regions from the country's south and southeast to its less fertile northern and western regions, including the 100,000 km² Ukrainian Polissia.

It is widely understood that the successful adoption of precision farming requires the identification and demarcation of spatially diverse areas within a field known as intra-field spatial heterogeneity zones (ISHZ). These zones are taken into consideration when carrying out various technological operations in crop production, as highlighted by research conducted by Córdoba et al. (2016) and Méndez-Vázqueza et al. (2019).

Considering the specific nature of land use and land tenure in Ukraine, as well as the specialization of agricultural enterprises, the most effective method for identifying intra-field heterogeneity zones is an approach that takes into account multiple soil characteristics. However, regardless of the specific approach and parameters used, Geographic Information Systems (GIS) and mathematical modelling methods such as Frequency Ratio (FR) and Shannon's Entropy (SE) provide a universal tool for identifying ISHZs. Although these methods have been extensively and effectively utilized for flood prediction (Arabameri et al., 2019; Arora et al., 2021), landslide susceptibility (Shano et al., 2020; Wubalem, 2021), and forecasting groundwater resources distribution (Al-Ruzouq et al., 2019; Chatterjee et al., 2020), their use in identifying of intra-field spatial heterogeneity zones remains relatively scarce.

Considering all of the above, the objective of this study is threefold: (1) to process initial data on soil parameters and generate thematic layers containing relevant attribute information; (2) to identify and map ISHZs with distinct land quality, based on a combination of soil parameters, using the FR and SE modelling techniques; and (3) to compare the outcomes of both methods to determine which one is most effective in detecting ISHZs.

MATERIALS AND METHODS

The studies were carried out in 2021-2022 in the Menkivka starostynsky okrug Radomyshl community of Zhytomyr raion (Zhytomyr oblast, Ukraine). The study area is a part of the Zhytomyr physical-geographical region of the Ukrainian Polissia and located between 50°37´ to 50°3´ N and 29°08´ to 29°12´ E and spreads in an area of 6.59 km^2 (31.8% of total arable land) (Figure 1).

The climate of the study area is temperate (Dfb due to Köppen-Geiger climate classification).

The soil cover of the study area is represented by Dystric Leptosols (0.28 km^2), Anthric Luvisols (3.44 km^2), Anthric Retisols (0.23 km^2) and Umbric Gleysols (2.65 km^2) (according to the international soil classification system (WRB, 2014) and has a predominantly sandy-loamy texture.

A total of 145 geo-referenced representative surface soil samples at 0-20 cm depth were collected within the territory of interest. The selection was carried out on an irregular grid. The samples were crushed, air-dried in shade at room temperature (~ 25°C), and passed through a 2 mm sieve for further analysis.

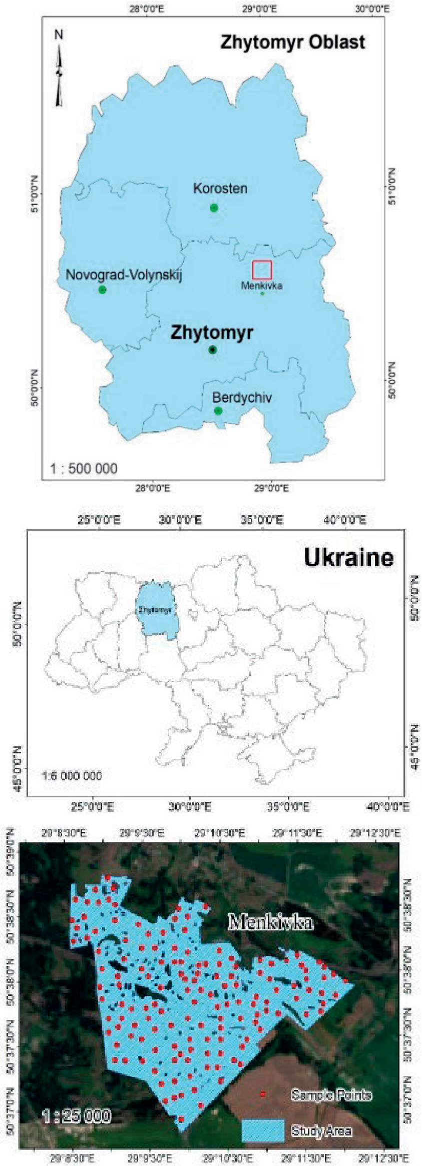

Figure1. Location of the study area

The following parameters were determined in each soil sample: humus content (Hu) - according to NSTU 4289:2004; pH_{KCl} (pH) - according to GOST 26483-85; cation exchange capacity (CEC) - according to ISO 11260:1994; calcium (Ca) and magnesium (Mg) - according to GOST 26487-85; hydrolytic acidity (Ha) - according to GOST 26212-91; nitrogen (N) - according to NSTU 7863:2015; phosphorus (P) and potassium (K) - according to NSTU

4405:2005; molybdenum (Mo) - according to GOST 50689-94; boron (B) - according to GOST 50688-94. The acid soluble (1N HCl extractant) forms of lead (Zn) and copper (Cu) were determined through the method of atomic and absorption spectrometry on the SOLAAR MkII-M6 Double Beam AAS device. The soil buffer balance index (SB) was determined by the Nadtochy method (Nadtochy, 1993).

To determine which soil parameter is best suited for identifying ISHZs, a multicollinearity analysis was conducted. The analysis utilized variance inflation factor (VIF) and tolerance (TOL) to assess whether the explanatory variables used in the modelling are highly dependent on one another.

The integration of thematic layers and their corresponding percentages was utilized to determine the spatial distribution of intra-field spatial heterogeneity through overlay analysis in an ArcGIS 10.8 environment. To prepare a spatial variability map for each soil variable, both geostatistical and deterministic methods were used for interpolation techniques. Geostatistical methods were used for hydrolytic acidity, the content of B and Mo, and the soil buffer balance index.

Cross-validation analysis was conducted to evaluate the accuracy of interpolation utilizing methods.

The optimal number of gradations of heterogeneity zones within the study area was established by the Principal Component Analysis (PCA) technique (Zeraatpisheh et al., 2020).

FR is defined as (Guru et al., 2017) (1):

$$FR = (W/TW)/(CP/TP) \quad (1)$$

where FR is a frequency ratio of the class of each soil parameter, W is the number of pixels of the most fertile and least fertile soil locations for each class of thematic maps; TW is the number of total pixels of the most fertile and least fertile soil locations in the study area; CP is the number of pixels in each thematic class and the TP is the total number of pixels in the study area. In the FR model, the FR value of each class in the thematic layer was considered as the weight of that particular class in thematic parameters to determine intra-field heterogeneity.

The SE for all the explanatory variables to prioritize the susceptibility of the individual explanatory variable to intra-field spatial heterogeneity forming and subsequent final susceptibility mapping has been calculated using the following equations (2-6):

$$P_{ij} = b/a \quad (2)$$

$$(P_{ij}) = \frac{P_{ij}}{\sum_{j=1}^{S_j} P_{ij}} \quad (3)$$

$$H_{ij} = -\sum_{j=1}^{S_j} (P_{ij}) \log_2 (P_{ij}),\ j = 1, \dots, n \quad (4)$$

$$I_j = \frac{H_{jmax} - H_{ji}}{H_{jmax}}, I = (0, 1), j = 1, \dots, n \quad (5)$$

$$W_j = I_j \cdot P_{ij} \quad (6)$$

where *a* is the class area of the independent variable and *b* is the area of the most fertile and least fertile soil locations falling within the class, expressed as a percentage, (P*ij*) is the probability of density, H_j and H_{jmax} represent entropy values, I_j is the information coefficient. W_j represents the resultant weight value for the factor as a whole.

Microsoft Excel program was used in the calculation of the FR and SE of the total input factors and the spatial analyst module of ArcGIS 10.8 has been used to reclassify and the final intra-field spatial heterogeneity zones maps were produced using a raster calculator.

Receiver Operating Characteristic (ROC) was chosen as the method for estimating model performance. In this method, for every possible cut-off value, false positive rates (FPR) and true positive rates (TPR) were plotted on the x-axis and y-axis, respectively (7), (8):

$$FPR = FP/(FP+TN) \quad (7)$$

$$TPR = TP/(TP+FN) \quad (8)$$

where FP is the number of false positive cases, TN is the number of true negative cases, TP is the number of true positive cases, and FN is the number of false negative cases. The FPR also termed sensitivity (Arabameri et al., 2019), is the probability a test will render an intra-field spatial heterogeneity when it exists and the TPR, which is also known by the name

"1-specificity" indicates one minus the probability a test will be negative in case of actually non-occurrence of intra-field spatial heterogeneity. Hence, in ROC, the sensitivity is plotted as a function of the false positive rate for various levels of cut-off points meaning thereby, each point on ROC is a sensitivity/specificity pair connected to a particular decision threshold (Arora et al., 2021).

The area under the curve (AUC) represents the discriminatory power of a model with which it accurately predicts the occurrence or non-occurrence of intra-field spatial heterogeneity. AUC values of <0.6, 0.6-0.7, 0.7-0.8, 0.8-0.9, and >0.9 indicate, respectively, poor, moderate, good, very good, and excellent model performance (Nhu V.H. et al., 2020).

The ROC curve and the AUC were calculated using the ROC Tool of ArcSDM.

RESULTS AND DISCUSSIONS

At the outset, the study planned to utilize 14 soil parameters. However, after conducting the multicollinearity analysis, it was found that variables like humus content, $pH_{(KCl)}$, cation exchange capacity (CEC), Ca, and Mg content had high multicollinearity with VIF>10 and TOL <0.1, and were excluded from the analysis. The VIF and TOL values for all the variables ranged from 1.60 to 8.13 and 0.121 to 0.62, respectively, as shown in Figures 2 and 3.

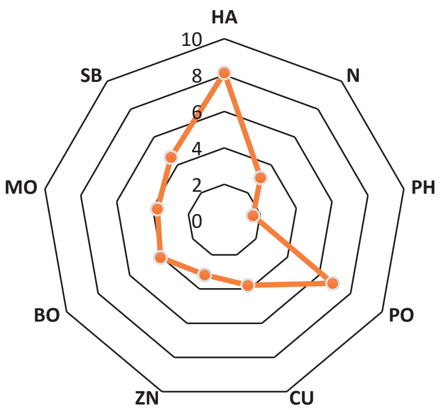

Figure. 2. Multicollinearity analysis of the soil parameters (VIF)

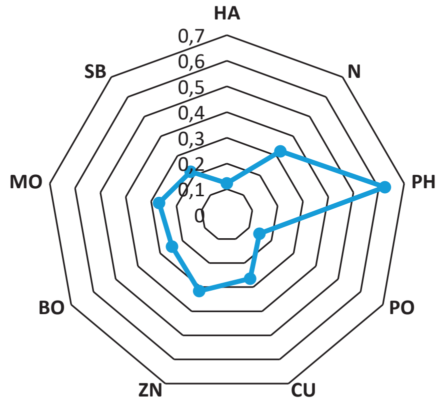

Figure. 3. Multicollinearity analysis of the soil parameters (TOL)

Then deterministic and geostatistical interpolation methods were used to visualize the spatial distribution of nine soil parameters. Thus, nine raster images were generated as a result and then were utilized as the fundamental geospatial data to carry out the forecasting of intra-field spatial heterogeneity (Figures 4-12).

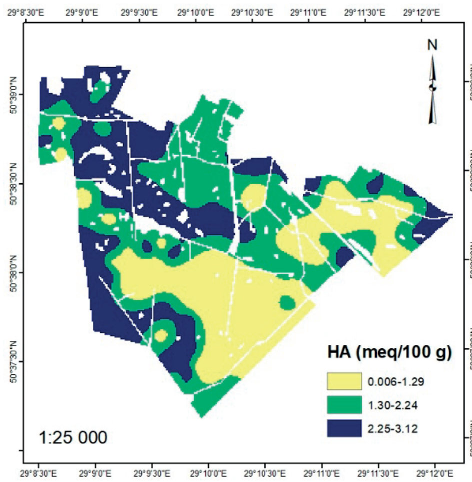

Figure 4. Intra-field spatial heterogeneity factors (soil parameters) used in this study: hydrolytic acidity

It is important to point out that the southeastern and eastern areas of the study area exhibit the highest values for all of the soil parameters examined, whereas the land parcels with lower values are primarily concentrated in the northwestern and western areas.

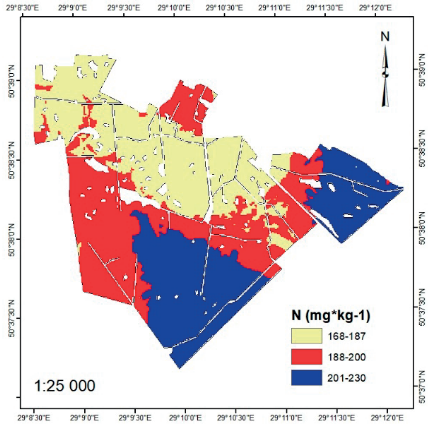

Figure 5. Intra-field spatial heterogeneity factors (soil parameters) used in this study: nitrogen

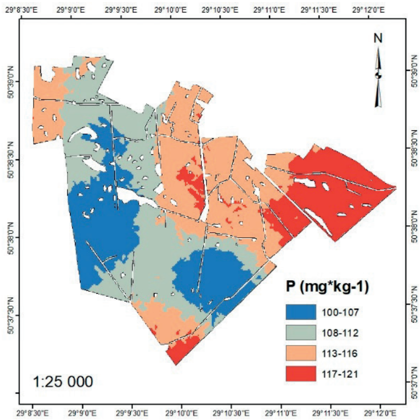

Figure 6. Intra-field spatial heterogeneity factors (soil parameters) used in this study: phosphorus

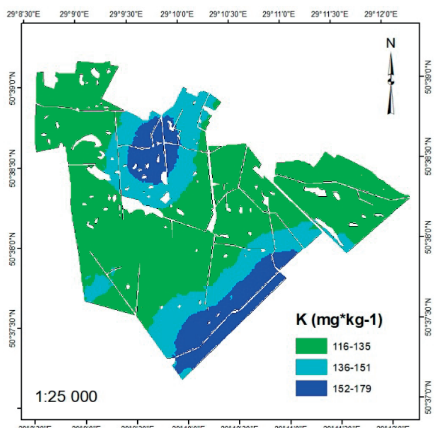

Figure 7. Intra-field spatial heterogeneity factors (soil parameters) used in this study: potassium

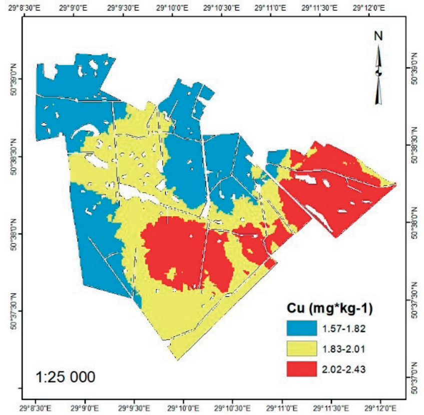

Figure 8. Intra-field spatial heterogeneity factors (soil parameters) used in this study: copper

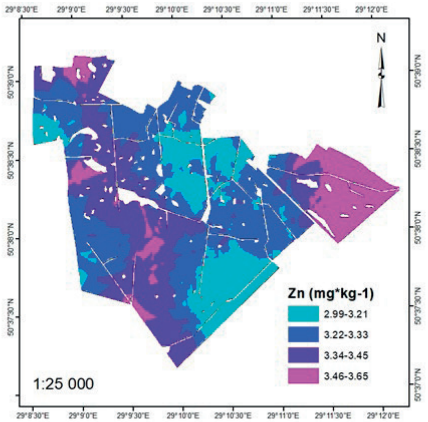

Figure 9. Intra-field spatial heterogeneity factors (soil parameters) used in this study: lead

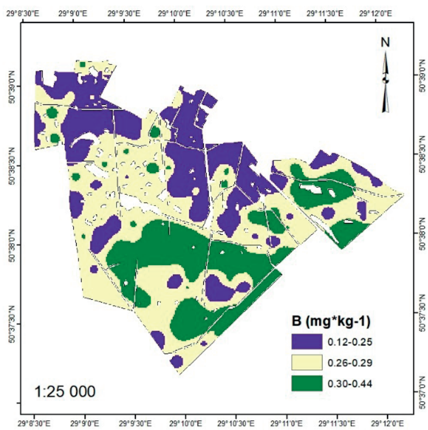

Figure 10. Intra-field spatial heterogeneity factors (soil parameters) used in this study: boron

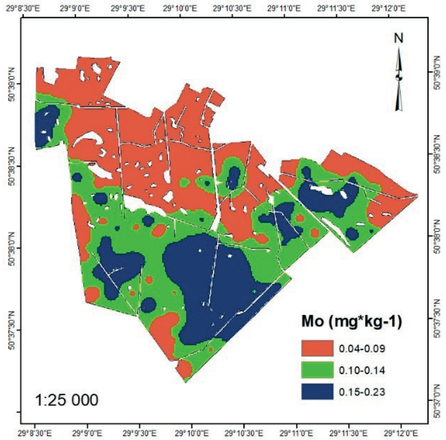

Figure 11. Intra-field spatial heterogeneity factors (soil parameters) used in this study: molybdenum

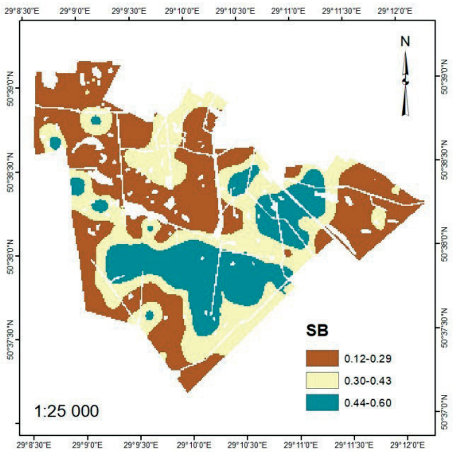

Figure 12. Intra-field spatial heterogeneity factors (soil parameters) used in this study: soil buffer balance index

This variability is largely attributed to the diverse soil cover, which comprises four different types of soil based on the FAO classification and eleven different types of soil according to the national classification system used in Ukraine.

To determine the appropriate number of categories for the intra-field spatial heterogeneity zones, PCA was applied. The principal components (PCs) with eigenvalues greater than 1 and accumulative contributions exceeding 60% were chosen (Oldoni et al., 2019; Srinivasan et al., 2022). Only the first three PCs were selected based on this criterion, which explained a total variability of 76.21% (Table 1).

Table 1. Principal component analysis for soil parameters

Principal compo nents	Eigenvalues	Component loadings (%)	Cumulative loadings, (%)
PC1	3.98	44.20	44.20
PC2	1.92	21.32	65.52
PC3	1.19	10.69	76.21
PC4	0.82	9.09	85.31
PC5	0.52	5.73	91.03
PC6	0.37	4.15	95.18
PC7	0.24	2.67	97.85
PC8	0.14	1.57	99.42
PC9	0.05	0.58	100.0

Frequency ratio is a susceptibility model that is commonly used and operates on the premise that the ratio of two event frequencies is a more effective predictor of the likelihood of those events occurring than the frequencies alone. In cases where the FR value for a soil parameter is higher, it suggests a strong correlation between the dependent variable (intra-field spatial heterogeneity zone) and the independent variable (the soil parameter in question). Conversely, FR values less than 1 indicate a weak relationship between the two variables (Tehrany et al., 2013).

The levels of phosphorus and zinc in the study area were categorized into four different classes, while the other soil parameters were divided into three classes, as shown in Table 2.

The highest frequency ratio values for indicators such as potassium, boron, copper, molybdenum, and soil buffer balance index were found in the upper categories (class 3). On the other hand, the maximum frequency ratio values for phosphorus, zinc, and hydrolytic acidity in the soil were observed in the lower categories (class 1), while the content of nitrogen showed the highest frequency ratio in the medium categories (class 2).

The highest prediction rate (5.667) was achieved for the phosphorus content, while the lowest prediction rate (2.423) was obtained for the zinc content. Based on these prediction rates, the studied soil parameters can be arranged in descending order as follows: P > SB > K > Mo > N > B > Ha > Cu > Zn.

Table 2. Intra-field spatial heterogeneity zones, computed using frequency ratio (FR)

Soil parameter	Class of soil parameter	Frequency Ratio (FR)	Prediction Rate (PR)
B	0.12–0.25	0.460	3.525
	0.26–0.29	2.400	
	0.30–0.44	3.452	
Cu	1.57–1.82	0.877	2.692
	1.83–2.01	0.721	
	2.02–2.43	1.147	
Mo	0.04–0.09	0.486	4.549
	0.10–0.14	1.182	
	0.15–0.23	3.413	
Ha	0.006–1.29	2.667	3.345
	1.30–2.24	0.584	
	2.25–3.12	0.527	
SB	0.12–0.29	0.141	5.483
	0.30–0.43	1.607	
	0.44–0.60	1.888	
N	168–187	0.489	4.328
	188–200	0.571	
	201–230	0.489	
P	100–107	1.733	5.667
	108–112	1.512	
	113–116	0.869	
	117–121	0.494	
K	116–135	0.379	4.652
	136–151	1.127	
	152–179	8.596	
Zn	2.99–3.21	4.265	2.423
	3.22–3.33	0.692	
	3.34–3.45	0.647	
	3.46–3.65	0.305	

To identify the intra-field spatial heterogeneity zones using Shannon's entropy modelling, each of the nine soil parameters was assigned a weight (W_j) based on Equation (6) of the SE model. The highest weight was assigned to the soil phosphorus content (5.456), while the lowest weight was assigned to copper (0.046) (Table 3).

The maximum probability density (P_{ij}) was determined for the lower categories (class 1) based on the levels of phosphorus, zinc, and hydrolytic acidity in the soil, while the remaining parameters showed the highest probability density in the upper categories (class 3). Based on the assigned weights, the soil parameters can be arranged in descending order as follows: K >N > Zn > Mo > B > Ha > SB > P > Cu.

Table 3. Intra-field spatial heterogeneity zones, computed using Shannon's entropy (SE)

Soil parameter	(P_{ij})	H_j for each	H_j (total)	H_{jmax}	I_j	P_{ij} (all)	W_j
B	0.07	0.28	1.28	1.59	0.19	6.31	1.21
	0.38	0.53					
	0.55	0.48					
Cu	0.32	0.53	1.56	1.59	0.02	2.75	0.05
	0.26	0.51					
	0.42	0.53					
Mo	0.10	0.32	1.20	1.59	0.24	5.08	1.24
	0.23	0.49					
	0.67	0.39					
Ha	0.71	0.36	1.17	1.59	0.26	3.78	0.99
	0.16	0.42					
	0.14	0.40					
SB	0.04	0.18	1.19	1.59	0.25	3.64	0.90
	0.44	0.52					
	0.52	0.49					
N	0.06	0.23	0.65	1.59	0.59	8.78	5.17
	0.07	0.26					
	0.88	0.16					
P	0.38	0.53	1.86	2.00	0.07	4.61	0.33
	0.33	0.53					
	0.19	0.45					
	0.11	0.35					
K	0.04	0.18	0.73	1.59	0.54	10.10	5.46
	0.11	0.35					
	0.85	0.20					
Zn	0.72	0.34	1.27	2.00	0.36	5.91	2.15
	0.12	0.36					
	0.11	0.35					
	0.05	0.22					

While FR model is typically utilized for evaluating landslide susceptibility (Abdo et al., 2022; Babitha et al., 2022), flood hazard assessment (Pawar et al., 2022; Isiaka et al., 2023), or identifying potential groundwater areas (Guru et al., 2017; Olajide et al., 2022), in the current study, it exhibited strong performance for detecting ISHZs (Figure 13) with an accuracy rate of up to 82% (as demonstrated in Figure 14).

To implement Shannon's entropy model for ISHZ detection, it is necessary to compute the entropy value for each site in the study area based on the selected soil parameters determined by the multicollinear analysis. Parcels with the highest entropy value will display the greatest discrepancies in soil parameters, while parcels with the lowest entropy will show the greatest uniformity in soil parameters.

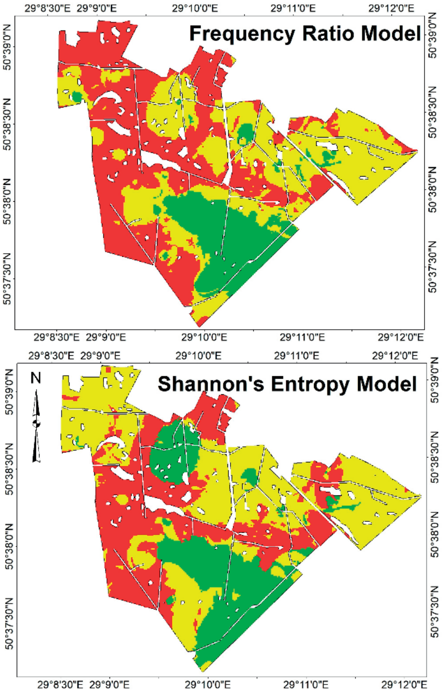

Figure 13. Zones of intra-field spatial heterogeneity with corresponding soil quality (red – low quality; yellow – moderate quality; green – high quality)

Despite the fact that Shannon's entropy model is often utilized for predicting groundwater levels (Razzagh et al., 2021), forecasting flood-prone areas (Haghizadeh et al., 2017), and assessing the degree of urban expansion in various regions (Das & Angadi, 2020), it can be effectively employed to predict the presence of ISHZs with up to 84% precision, as shown in Figure 15.

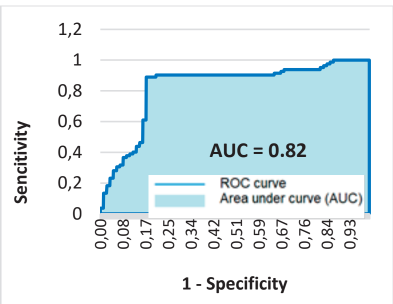

Figure 14. Performance of the model for the spatial prediction of intra-field heterogeneity zones using the ROC curve technique and AUC for FR model

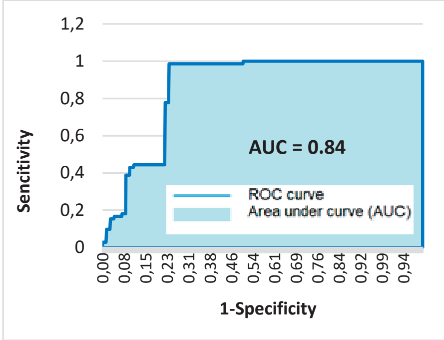

Figure 15. Performance of the model for the spatial prediction of intra-field heterogeneity zones using the ROC curve technique and AUC for SE model

As a result of the performed studies, it was found that the efficiency of the FR model is lower than the efficiency of the SE. However, given its ease of use as well as its robustness to small sample sizes, the FR model can be used to pre-detect the presence of ISHZs and is the best choice for analyzing datasets with a limited number of observations.

As previously mentioned, there is currently no universal method for identifying intra-field spatial heterogeneity zones, and different techniques have been proposed by researchers (Oshunsanya et al., 2017; Kutsayeva & Myslyva, 2020). This study focused solely on an approach based on the chemical properties of the soil, and the list of soil parameters used is not exhaustive and can be expanded depending on the availability of geospatial data on soil properties and the requirements for identifying ISHZs.

CONCLUSIONS

While both the SE and FR models demonstrated high accuracy in identifying intra-field heterogeneity zones, the SE model performed better and has significant potential for mapping these zones not only within Ukraine's Polissia region but also in neighbouring countries with similar soil cover parameters. Therefore, we recommend using the SE model for identifying intra-field heterogeneity zones as a tool to enable agricultural enterprises of different ownership structures to implement precision farming practices, including variable rate (VR) technologies, more effectively.

Future studies should prioritize carrying out field trials with crops using a crop rotation approach to validate the obtained outcomes and to provide more clarity on the established limits of the identified intra-field spatial heterogeneity zones.

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