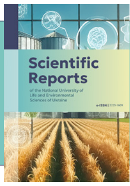
Received 28.11.2025 Revised 26.02.2026 Accepted 23.04.2026 Published: 30.04.2026

Vol. 22, No. 2
2026



Scientific Reports of the National University of Life and Environmental Sciences of Ukraine

Journal homepage: https://scireports.com.ua/en e-ISSN 2223-1609

UDC 633.15:631.55 DOI: 10.31548/dopovidi/2.2026.51

Justification for the delineation of field productivity zones based on long-term monitoring of maize yield and satellite data

Lesia Harbar
PhD in Agricultural Sciences, Associate Professor
National University of Life and Environmental Sciences of Ukraine
03041, 15 Heroiv Oborony Str., Kyiv, Ukraine
https://orcid.org/0000-0003-4249-0434

Bohdan Vaskivskyi*
Postgraduate Student
National University of Life and Environmental Sciences of Ukraine
03041, 15 Heroiv Oborony Str., Kyiv, Ukraine
https://orcid.org/0009-0003-6852-3844

Abstract. The article presents the results of a long-term analysis of the spatial heterogeneity of maize (*Zea mays* L.) yield in a production field with an area of 448 hectares located in the transition zone between Polissia and the Forest-Steppe of Ukraine. The study was conducted using yield maps from 2019-2020 and 2023-2024 with the aim of assessing the stability of within-field productivity zones and establishing their relationship with satellite data. The spatial structure of productivity was analysed by aggregating yield monitor data into a regular 20 × 20 m grid, followed by classification into three productivity zones. To confirm the agroecological basis of the zones, long-term NDVI composites (Sentinel-2) and maps of soil surface brightness were used. It was found that the spatial boundaries of low, medium, and high productivity zones remained consistent throughout the entire study period, despite interannual fluctuations in the average yield level. The long-term mean values were 6.2 t/ha in the low, 9.5 t/ha in the medium, and 12.3 t/ha in the high productivity zone. The coefficient of variation of zone areas did not exceed 11.6%, indicating their high spatial and temporal stability. Correlation analysis revealed a strong positive relationship between the long-term productivity map and the long-term average NDVI (r = 0.86-0.94), as well as a stable inverse relationship with soil brightness indicators (r = -0.79 to -0.87). High values of the coefficient of determination (R^2 = 0.74-0.88) confirm that the main share of spatial yield variation is driven by persistent soil and landscape factors. The

Suggested Citation:
Harbar, L., & Vaskivskyi, B. (2026). Justification for the delineation of field productivity zones based on long-term monitoring of maize yield and satellite data. *Scientific Reports of the National University of Life and Environmental Sciences of Ukraine*, 22(2), 51-64. doi: 10.31548/dopovidi/2.2026.51.

**Corresponding author*

obtained results demonstrate the feasibility of using long-term yield maps in combination with satellite indices for the delineation of stable field productivity zones. This approach provides a scientific basis for the implementation of precision agriculture technologies and spatially differentiated management of agricultural resources

Keywords: *Zea mays* L.; spatial heterogeneity of the field; soil brightness; long-term yield maps; coefficient of determination; precision agriculture; management zones

Introduction

In the current context of intensified farming and increasing spatial heterogeneity of agricultural landscapes, the scientifically informed delineation of productivity zones within a single field is becoming particularly relevant. Intra-field variability in soil properties, micro-relief, water regime and nutrient availability creates persistent spatial differences in crop growth and productivity, which cannot be effectively accounted for when using standardised agronomic solutions. In this context, the role of precision farming approaches is growing, aimed at identifying homogeneous management zones based on spatial data and the subsequent adaptation of technological operations to local field conditions.

The combination of geostatistical approaches with multivariate analysis is effective for identifying intra-field management zones based on a set of soil indicators. Thus, H.M. Salem *et al.* (2024), based on spatial analysis of soil characteristics (in particular pH, organic matter, cation exchange capacity, electrical conductivity, and macro- and microelement content) and subsequent clustering, demonstrated the possibility of forming zones with similar characteristics that differed in terms of crop productivity. This confirms that accounting for intra-field variability is a key factor in improving the accuracy of nutrient management and resource efficiency.

The instrumental capabilities of geoinformation technologies for the formation of agromanagement zones are detailed in the work of M.M. Elsharkawy *et al.* (2022), where it is demonstrated that GIS approaches and spatial multi-criteria procedures enable the integration of heterogeneous data layers (soil, topography, productivity) and can be used as a basis for decision-making regarding the differentiated application of resources in precision farming systems.

A separate line of research is devoted to analysing the causes and consequences of sub-field yield stability/variability over time. S.J. Leuthold *et al.* (2024) demonstrated that zones of yield stability may differ in structure and soil organic matter controls (the ratio and dynamics of the POM and MAOM soil fractions), highlighting the complex nature of the interaction between edaphic factors, productivity and organic matter transformation processes at the sub-field level. This justifies the use of long-term data as a basis for identifying zones aimed at stable management decisions. An important aspect of zoning is the use of Earth remote sensing as a source of timely and spatially continuous indicators of crop condition.

Research by N. Narra *et al.* (2022) showed that open-access satellite data can be used to identify field zones with stable and variable characteristics throughout the growing season based on spectral indicators, creating the conditions for integrating satellite data with yield data in spatial management tasks. In addition to soil-relief and satellite indicators, precision farming approaches are used to validate zones using biologically and technologically significant indicators. M.A. de Oliveira Filho *et al.* (2025) demonstrated that open-access satellite data can be used to identify field zones with stable and variable characteristics during the growing season based on spectral indicators, creating opportunities for integrating satellite-derived metrics with yield data in spatial management applications. In addition to soil, topographic, and satellite indicators, precision agriculture approaches also employ biological and technologically relevant parameters for zone validation. The practical value of the zonal approach becomes apparent when zones form the basis for differentiated technological solutions.

In particular, research by F.A. Baron *et al*. (2025) demonstrated on a heterogeneous field that the optimal maize plant density varies between productivity zones, and that adjusting plant population density to account for these zones can serve as a tool for improving both agronomic and economic performance. At the same time, zoning based on soil electrical conductivity reflects differences in particle size distribution and physical properties and can be useful for justifying sowing adjustments within a field, highlighting the importance of soil environment proxy indicators for technological adaptation. However, the effectiveness of zonal management depends on the combination of spatial decisions with weather conditions and the farming system.

M.M. Mikha *et al*. (2024) demonstrated in their work that a zoned approach to differentiated nitrogen application in a dryland system yields a positive response in years with favourable moisture conditions, whereas during periods of low rainfall, the effectiveness of the technology decreases, indicating the need to account for climatic factors when interpreting the results of zonal management and planning differentiated technologies. Despite a significant body of research in the field of zoning and precision farming, the issue of using long-term yield maps as a basic tool for identifying stable productivity zones within a production field, with subsequent verification by satellite data, remains insufficiently addressed. Of particular relevance is determining the degree of spatio-temporal stability of such zones under production conditions.

In this regard, the aim of the study was to assess the possibility of identifying stable productivity zones within a production field based on long-term maize yield maps and to confirm their agro-ecological determinants using satellite indicators.

Materials and Methods

The study was conducted in accordance with the principles of the Convention on Biological Diversity (1992), in particular the provisions of Article 7, which regulates the monitoring of biodiversity components and the systematisation of relevant spatial data. The application of long-term remote monitoring of yield and satellite indices was consistent with approaches aimed at the sustainable use of agroecosystems and the minimisation of negative anthropogenic impacts on the productive potential of land. The object of the study was a commercial field with an area of 448 ha, located within the territory of LLC Chernihiv Industrial Dairy Company in Chernihiv District, Chernihiv Region, in the transition zone between Polissia and the Forest-Steppe of Ukraine. Throughout the entire study period, the field was planted with the maize hybrid DKS 3939 under the farm's standard uniform production technology. The use of a stable cultivation system made it possible to minimise the influence of agronomic differences on the formation of the spatial yield structure.

The analysis of the spatial structure of productivity was carried out using long-term maize yield maps for 2019-2020 and 2023-2024. Primary yield data were obtained during harvest using a combine harvester equipped with an automatic yield monitoring system and GPS-based satellite positioning. During harvesting, spatially referenced yield records were generated, containing coordinates, yield values, and combine movement parameters. The primary yield data underwent a preprocessing procedure. Anomalous values caused by machinery turning, uneven combine speed, or technical measurement errors were removed from the dataset. Filtering was performed by excluding values outside the statistically acceptable interval determined on the basis of the interquartile range. After cleaning, the data were aggregated into a regular spatial grid. The spatial grid was created using the geographic information system QGIS (version 3.x). The field area was divided into a regular square grid with a cell size of 20 × 20 m. For each cell, the mean yield value was calculated based on all yield monitor points falling within its boundaries. This approach ensured comparability of spatial data across different years of observation.

The long-term productivity map was generated by calculating the mean yield value for each grid cell across all years of the study. The resulting raster was then used for the further delineation of productivity zones. Classification was performed on the basis of relative yield values. For this purpose, yield values were normalised relative to the field mean and divided into three classes: low, medium, and high productivity levels. To ensure correct interannual comparison of spatial patterns, a unified yield gradient scale (from <4.0 to ≥13.0 t/ha) was applied across all study years. For additional assessment of the spatial field structure, satellite indicators were used. In particular, maps of the normalised difference vegetation index (NDVI) derived from Sentinel-2 satellite imagery were analysed. For each study year, composite images representing the period of active crop vegetation were generated. Satellite data processing was performed using QGIS tools and software scripts written in Python.

Within the Python environment (version 3.x), the libraries GDAL, Rasterio, GeoPandas, NumPy, and Pandas were used for spatial data processing. These tools were employed for downloading satellite imagery, calculating NDVI, spatial clipping of data to the boundaries of the study field, and generating long-term rasters. In addition, soil surface brightness maps were used to analyse soil conditions; these were derived from satellite images obtained during periods of minimal vegetation cover. Such imagery made it possible to assess the spatial heterogeneity of surface soil properties. Following the processing of satellite data, all raster indicators (NDVI and soil brightness) were normalised to a relative scale of 0-100 using linear scaling (min-max normalisation). This ensured comparability between different sources of spatial information and enabled their integrated analysis.

The assessment of the spatial and temporal stability of the productivity structure was carried out by comparing the areas of productivity zones between study years. For this purpose, the coefficient of variation (CV) of zone areas was calculated using the formula:

$$\mathrm{CV} = \mathrm{SD} / \mathrm{Mean} \times 100\%, \tag{1}$$

where SD – the standard deviation of the area of the zone between years, and Mean – the average area of the corresponding zone. Statistical analysis of the relationship between yield maps, NDVI values and soil brightness indices was performed using Pearson's correlation coefficient. The proportion of spatial variation in yield explained by satellite indicators was assessed using the coefficient of determination R^2. Statistical calculations were performed in Python using the SciPy and Statsmodels libraries. Visualisation of spatial data, creation of thematic maps and analysis of productivity structure were carried out in the QGIS environment.

Results

As shown in Figure 1, analysis of yield maps indicates a consistent spatial recurrence of zones with varying levels of productivity throughout the entire observation period. CV of the areas of these zones between years served as a quantitative criterion of spatial stability: for the low-productivity zone it was 7.9%, for the medium-productivity zone 2.9%, and for the high-productivity zone 11.6%, which corresponds to a low level of inter-annual variability in the spatial structure of the field. In all the years studied, areas with consistently low yields (red and yellow tones) are clearly discernible, as are zones of medium and high productivity (light and dark green tones), which retain their spatial position.

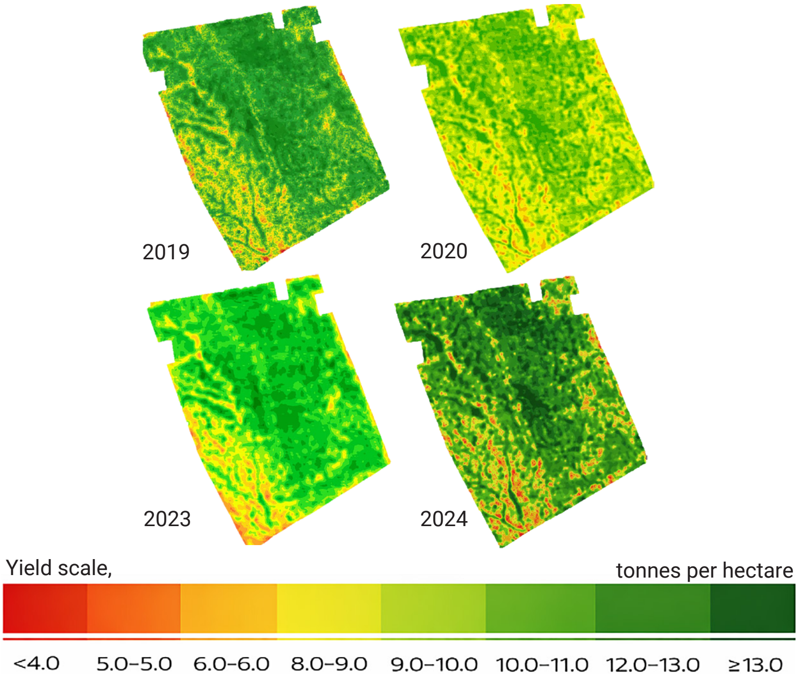


Figure 1. *Spatial heterogeneity of field yield based on long-term data*

Source: authors' own research

At the same time, the intensity of productivity expression varied between years, reflecting the influence of weather conditions and other annual factors. In particular, in 2020 a general decline in yield was observed compared with 2019 and 2024, whereas in 2024 the largest share of high-yielding areas was recorded, namely 33% or 147.8 ha with yields exceeding 11 t/ha. Despite this, the spatial boundaries of low- and high-productivity zones remained stable: the average percentage of spatial overlap between zones in adjacent years was 73.5%, specifically 80.0% for the medium-productivity zone, 69.8% for the low-productivity zone, and 66.5% for the high-productivity zone, indicating the dominant influence of stable soil and topographic factors. The obtained results confirm the feasibility of using long-term yield maps as a reliable basis for delineating field productivity zones, which can be applied for the further differentiation of cultivation practices, in particular seeding rates.

Figure 2 presents a comparison between the soil surface brightness map and the long-term field productivity map constructed from satellite data. Visual analysis indicates consistency in spatial patterns between areas with differing soil brightness and levels of crop productivity. In particular, zones of reduced productivity generally correspond to areas with higher soil surface brightness, indirectly reflecting differences in soil properties and water regime. The obtained results confirm that spatial differences in yield have a stable soil-landscape basis and are consistent with long-term satellite data, which strengthens the justification for using long-term yield maps to delineate field productivity zones. The correlation analysis data (Table 1) indicate a strong relationship between the long-term field productivity map and soil brightness indicators. The values of the correlation coefficient between productivity estimated using the NDVI and the productivity map ranged from 0.86 to 0.94, indicating a very high degree of spatial agreement between satellite-derived indicators and the actual yield structure of the field. Such correlation values suggest that the NDVI reliably reflects differences in crop condition and productivity levels within the studied area.

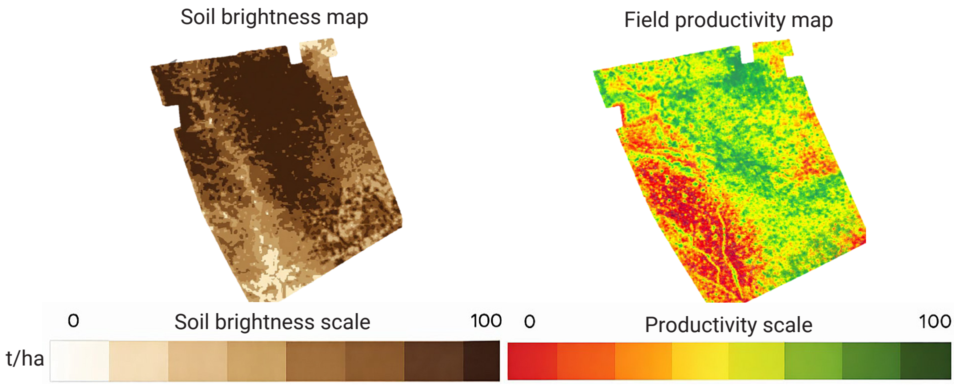


Figure 2. *Spatial heterogeneity of maps showing long-term field productivity and soil brightness*

Source: author's own research

Table 1. *Correlation relationships between long-term field productivity (NDVI) and soil brightness indicators*

Year/ Indicator	Correlation coefficient with the productivity map (long-term average NDVI), r	Correlation coefficient with the soil brightness map, r	Coefficient of determination (R^2)	Moran's I of residuals
2019	0.92	-0.84	0.85	0.18
2020	0.86	-0.79	0.74	0.28
2023	0.91	-0.82	0.83	0.15
2024	0.94	-0.87	0.88	0.12
Mean	0.91	-0.83	0.82	0.18

Source: authors' own research

High correlation coefficients were observed in all years of the study, confirming the stability of the identified patterns. The highest value (r = 0.94) was recorded in 2024, whereas in 2020 the correlation was slightly lower (r = 0.86), which may be associated with less favourable weather conditions during that season and an overall reduction in yield levels. Nevertheless, even under such conditions, the strength of the relationship remained high, confirming the suitability of satellite indices for analysing the spatial structure of crop productivity.

The mean value of the correlation coefficient between NDVI and the productivity map was 0.91, indicating a very strong relationship between vegetation indices and actual yield indicators. This suggests that satellite data can be effectively used to identify field productivity zones and to analyse within-field heterogeneity of agroecosystems. At the same time, a stable inverse relationship was identified between the productivity map and soil brightness (r = -0.79 to -0.87), indicating a decrease in productivity in areas with higher soil surface brightness. This relationship may be explained by the fact that lighter-coloured soils often have lower organic matter content, reduced water-holding capacity, or a coarser texture, which limits plant development and reduces yield formation potential. Accordingly, darker soil areas generally possess more favourable agrophysical and agrochemical properties, creating better conditions for the growth and development of maize plants.

Analysis of the obtained coefficients shows that the strength of the inverse relationship between soil brightness and productivity was stable across all years of the study. The highest absolute correlation coefficient (r = -0.87) was observed in 2024, indicating a particularly clear manifestation of soil factors influencing yield formation under favourable growing conditions. In 2020, this value was slightly lower (r = -0.79), which may be associated with an increased influence of weather factors on yield formation. High values of the coefficient of determination (R^2 = 0.74-0.88) confirm that a substantial proportion of the spatial variation in field productivity is explained by the analysed factors. In particular, from 74% to 88% of yield variability in different years can be attributed to spatial field characteristics reflected in NDVI values and soil surface brightness. The mean value of the coefficient of determination was 0.82, indicating a high explanatory power of the model and confirming the significant role of soil characteristics in shaping the spatial structure of productivity.

To verify the reliability of the correlation analysis, Moran's I index was calculated for the regression residuals, that is, for the difference between the actual yield values and those predicted by the model based on NDVI for the respective year. If the residuals are spatially random (Moran's I ≈ 0), this indicates that the model adequately describes the spatial structure of the field and that autocorrelation does not distort Pearson correlation coefficients. A substantial decrease in the index from the initial level of 0.70 (for yield) to an average value of 0.18 (for regression residuals) confirms that the NDVI of the respective year adequately captures the main spatial structure of field yield. The weak level of residual autocorrelation indicates the absence of significant bias in the model parameter estimates and confirms the statistical reliability of the obtained correlations. Thus, the results of the correlation analysis confirm a close relationship between satellite-derived indicators of crop condition, soil surface characteristics, and actual maize yield. The identified patterns indicate that spatial differences in productivity have a stable soil-landscape basis and can be effectively identified using remote sensing methods. This provides a scientific foundation for the use of satellite data and long-term yield maps in precision agriculture for the delineation of productivity zones and optimisation of agronomic practices within the field. The data presented in Table 2 indicate a clearly expressed spatial heterogeneity of maize yield within the studied field and its stability over multiple years.

Table 2. *Characteristics of field productivity zones based on long-term yield data*

Year	Zone	Number of cells, units	Yield, t/ha	SD, t/ha	Coefficient of variation (CV), %	Zone area	
						ha	%
2019	Low	2,912	6.2	0.84	13.5	116.5	26
	Medium	4,928	9.4	0.71	7.6	197.1	44
	High	3,360	12.6	1.12	8.9	134.4	30
2020	Low	3,248	5.0	0.92	18.4	129.9	29
	Medium	5,152	8.2	0.78	9.5	206.1	46
	High	2,800	10.5	1.05	10.0	112.0	25
2023	Low	3,024	6.5	0.79	12.2	121.0	27
	Medium	5,040	9.8	0.65	6.6	201.6	45
	High	3,136	12.4	0.98	7.9	125.4	28
2024	Low	2,688	7.0	0.81	11.6	107.5	24
	Medium	4,816	10.5	0.69	6.6	192.6	43
	High	3,696	13.8	1.21	8.8	147.8	33

Table 2. *Continued*

Year	Zone	Number of cells, units	Yield, t/ha	SD, t/ha	Coefficient of variation (CV), %	Zone area	
						ha	%
Mean	Low	2,968	**6.2 ± 0.83***	0.84	13.9	121.0	27
	Medium	4,984	**9.5 ± 0.94***	0.71	7.6	201.6	45
	High	3,248	**12.3 ± 1.34***	1.09	8.9	129.9	29
CV for zone areas (%): 7.9 for the low zone; 2.9 for the medium zone; 11.6 for the high zone.							

Note: * – 95% confidence interval; differences between all pairs of zones are statistically significant (Welch's test, $p < 0.01$)
Source: authors' own research

The results showed that throughout all years of observation, the high-productivity zone was characterised by the highest yield levels, ranging from 10.5 to 13.8 t/ha, whereas in the medium-productivity zone yields ranged from 8.2 to 10.5 t/ha, and in the low-productivity zone from 5.0 to 7.0 t/ha. The mean values over the study period were 6.2, 9.5, and 12.3 t/ha for the low-, medium-, and high-productivity zones, respectively, confirming a consistent differentiation in productivity between the identified zones and indicating substantial differences in the yield potential of different parts of the field.

The difference between the long-term average yields of the high- and low-productivity zones was 6.1 t/ha, which corresponds to 65% of the mean field yield. Statistical analysis (Welch's test) confirmed the high significance of differences between all pairs of zones in all years of the study ($p < 0.01$). The long-term mean yields were 6.2 ± 0.83 t/ha (95% CI) for the low-productivity zone, 9.5 ± 0.94 t/ha for the medium-productivity zone, and 12.3 ± 1.34 t/ha for the high-productivity zone (Table 2). Such a gap in productivity indicates the presence of substantial differences in soil and agroecological conditions across different parts of the field, which determine the capacity of plants to form yield. Within a uniform agronomic management system, this implies that different areas of the field have unequal resource-use potential, creating a basis for the implementation of differentiated crop management practices.

Despite interannual fluctuations in the overall yield level of the field, the relationship between productivity zones remained relatively stable. In all years, a clear gradient in yield between low-, medium-, and high-productivity zones was maintained, indicating the stability of spatial differences in productivity. For example, even in 2020, which had the lowest average field yield (8.0 t/ha), the relative differences between zones persisted, and high-productivity areas continued to demonstrate significantly better performance compared with other parts of the field. Under more favourable conditions in 2024, this difference became even more pronounced, indicating the ability of high-productivity zones to more effectively realise their potential under optimal growing conditions.

Analysis of the area of productivity zones showed that the medium-productivity zone occupied the largest share of the field, averaging 45%. This zone forms the main body of the crop and is characterised by relatively stable yields close to the field average. The high-productivity zone accounted for an average of 29% of the field area, indicating a substantial proportion of land with elevated yield potential. At the same time, the low-productivity zone covered approximately 27% of the field and consistently exhibited lower yield levels.

A comparison of zone areas between years shows that their proportions varied only slightly. The share of the low-productivity zone ranged from 24% to 29%, the medium zone from 43% to

46%, and the high zone from 25% to 33%. Such stability in spatial distribution indicates that productivity boundaries are primarily determined by persistent environmental factors, such as soil properties, topography, and water regime, rather than random interannual weather variability. Additional evidence of spatial stability is provided by the low values of the CV of zone areas. The lowest variability was observed in the medium-productivity zone, with a CV of only 2.9%, indicating that its area remained nearly unchanged throughout the study period. For the low-productivity zone, this value was 7.9%, and for the high-productivity zone 11.6%, which also reflects a relatively stable spatial distribution within the field. Even for the most variable high-productivity zone, changes in area remained moderate and did not exceed a few per cent of the total field area.

Thus, the analysis of long-term yield data demonstrates a high degree of spatial stability in the productivity structure of the studied field. The identified zones are characterised not only by substantial differences in yield levels but also by relatively stable boundaries and areas across years. This confirms the suitability of using long-term yield maps for field zoning and provides a foundation for the application of differentiated agronomic practices within precision agriculture systems.

Discussion

The obtained results indicate the presence of a clearly expressed spatial structure of productivity within the studied field, manifested in the stable recurrence of zones with different yield levels over several years. Over four years of observations (2019, 2020, 2023, 2024), three productivity zones were consistently identified within the field, characterised by distinctly different mean yield levels (6.2, 9.5, and 12.3 t/ha for the low-, medium-, and high-productivity zones, respectively) and similar area proportions: on average 27% for the low-, 45% for the medium-, and 29% for the high-productivity zone. Low coefficients of variation in zone area between years (2.9-11.6%) indicate a high degree of spatial stability in the field's productivity structure, despite changes in overall yield levels between years. Similar patterns are confirmed by numerous recent studies on within-field yield variability in precision agriculture systems.

In particular, a large-scale study by B. Maestrini & B. Basso (2021) analysed more than 5,500 yield maps for various crops in the United States. The authors found that zones of consistently high and low productivity persist over many years, even under substantial interannual weather variability. The results of current study are consistent with these findings: the proportion of area belonging to individual productivity zones changed only slightly, and the difference between the average yield levels of the zones remained within the range of 5-7 t/ha throughout the study period. Similar results were reported by Adhikari *et al.* (2023), who identified stable and unstable productivity zones across nine fields based on four-year maize yield datasets. In this case, the share of the low-productivity zone also remained relatively constant (around 27%), which aligns with the concept of "fixed" low-performing areas determined by soil-landscape factors. Comparable conclusions were obtained in the study by F. Castaldi *et al.* (2021), which examined the relationship between long-term yield maps and weather conditions. The authors found that within-field spatial yield patterns persist even under significant variation in precipitation between years, while weather primarily affects the intensity of yield rather than the spatial configuration of productivity zones. A similar pattern was observed in the studied field: 2020 was characterised by a reduced mean yield (8.0 t/ha compared with 9.5-10.5 t/ha in other years), yet the boundaries of low-, medium-, and high-productivity zones remained close to their long-term configuration.

The role of soil properties in shaping spatial productivity heterogeneity is also supported by modelling results presented by I.M. Hernández-Ochoa *et al.* (2025). Based on a thirty-year simulation of crop yields, the authors showed that spatial variability driven by soil characteristics often exceeds interannual variability associated with weather conditions. In this study, this is further confirmed by the stable inverse relationship between productivity and soil surface brightness ($r = -0.79$ to -0.87), which indirectly reflects the influence of soil texture, organic matter content, and water-holding capacity on yield formation. The importance of integrating multiple sources of spatial information for productivity zoning is highlighted in the work of L.G.G. Sterle & J.P. Molin (2025). The authors demonstrated that combining historical yield maps with soil electrical conductivity data and topographic attributes improves the accuracy of management zone delineation. Similarly, the comparison of the long-term productivity map with the soil brightness map revealed a high degree of spatial agreement between these layers ($|r| \approx 0.8$-0.87, R^2 up to 0.88), indicating a stable soil-landscape control over the spatial structure of yield.

The high correlation values between NDVI indicators and the productivity map obtained in the study are consistent with the findings of A. Tamás *et al.* (2023). In this case, the long-term average NDVI showed a correlation with the productivity map in the range of $r = 0.86$-0.94 (mean 0.91), with a coefficient of determination R^2 between 0.74 and 0.88, indicating that a substantial proportion of spatial yield variability is explained by remote sensing vegetation indices. In the study by A. Tamás *et al.* (2023), NDVI derived from unmanned aerial vehicles demonstrated a strong positive relationship with maize yield ($r \approx 0.80$-0.84) during the late vegetative and early reproductive growth stages. Taken together, these findings indicate that NDVI can be effectively used as an indicator of the spatial structure of field-level productivity. Similar results were obtained in the study by D. Radočaj *et al.* (2025), which showed that Sentinel-2 vegetation indices can be used to assess the spatial variability of maize yield. The authors emphasised that the use of red-edge indices and phenological metrics improves the accuracy of correlations with actual yield maps. This is consistent with the observation that the integration of multi-year NDVI indicators, rather than single-date imagery, provides the best agreement with the field productivity structure.

At the same time, P. Killeen *et al.* (2024) highlighted the importance of accounting for spatial data structure when analysing relationships between satellite indicators and yield. The authors demonstrated that standard cross-validation approaches may lead to overestimation of model accuracy, whereas spatially explicit validation provides more realistic results. This underscores the need for caution when interpreting correlations between remote sensing indices and yield, particularly when correlation coefficients are high but not tested for spatial generalisability. Further evidence supporting the effectiveness of satellite indices for yield assessment is provided by B. Zhu *et al.* (2021), who showed that combining NDVI with meteorological data enables the development of more accurate maize yield prediction models at the regional scale. This approach integrates both the biophysical condition of crops and the influence of weather factors, significantly improving model explanatory power. Field-scale results align with this concept: NDVI provides the spatial framework of productivity, while interannual yield differences are largely explained by climatic variability.

Additional improvements in yield prediction accuracy are demonstrated in the study by S. Sarkar *et al.* (2025), which employed machine learning and multispectral data from unmanned platforms. The authors found that integrating satellite indicators with soil and topographic characteristics significantly enhances model performance. This confirms the importance of a comprehensive approach to analysing spatial variability in productivity. A similar principle is evident in this case, where the combination of long-term yield maps with satellite indicators and soil brightness maps enabled more reliable identification of stable productivity zones. Comparable findings were reported by S. Chen *et al.* (2022), who applied machine learning techniques to spatially disaggregate statistical maize yield data.

Their results showed that the use of multi-source datasets, including vegetation indices, climatic variables, and soil properties, allows accurate reconstruction of spatial yield patterns over large areas. Likewise, L. Miao *et al.* (2024) demonstrated the high effectiveness of multi-source data integration for maize yield prediction, showing that combining climatic, satellite, and soil indicators in machine learning models leads to high coefficients of determination. The authors emphasised that climatic factors define general spatial productivity trends, while remote sensing indices reflect the current physiological state of crops.

Thus, the obtained results support current scientific understanding of the formation of spatial productivity patterns in agricultural crops. It has been established that within-field yield variability is primarily driven by stable soil-landscape factors, whereas weather conditions mainly determine the intensity of productivity expression in individual years. High correlations between the long-term productivity map and NDVI ($r \approx 0.9$, $R^2 \approx 0.8$), together with a consistent inverse relationship with soil brightness, confirm that long-term yield maps combined with remote sensing vegetation indices represent an effective tool for delineating field productivity zones and optimising crop management practices in precision agriculture systems.

Conclusions

An analysis of long-term maize yield maps for the 2019-2020 and 2023-2024 periods showed that spatial variations in productivity within the study field are distinct and stable. Despite inter-annual variability in weather conditions and overall yield levels, the spatial distribution of low-, medium- and high-productivity zones remained consistent, indicating the dominant influence of soil and topographical factors in determining maize crop productivity. It was established that the high-productivity zone was characterised by the highest average yield values throughout the entire study period, whilst the medium-productivity zone occupied the largest share of the field area, and the low-productivity zone consistently exhibited the lowest yield levels. The interannual variation in the areas of the zones was insignificant, as confirmed by low values of the CV, and indicates a high spatial and temporal stability of the field's productivity structure.

A comparison of long-term yield maps with a soil surface brightness map and a long-term productivity map derived from average NDVI values revealed a high degree of consistency in spatial patterns. Areas of reduced productivity predominantly corresponded to plots with increased soil brightness and lower NDVI values, whereas highly productive plots were characterised by lower soil surface brightness and consistently high satellite productivity indices. This confirms the agroecological determinants of the identified zones and their relationship with soil properties and water regime. Correlation analysis revealed a close direct relationship between the map of long-term field productivity and the long-term average NDVI, as well as a consistent inverse relationship between productivity and soil brightness. High values of the coefficient of determination indicate that a significant proportion of the spatial variation in field productivity is explained by soil differences that are stable over time. The results obtained confirm the validity of using long-term yield maps as a reliable and informative basis for identifying field productivity zones. Combining yield monitoring data with satellite productivity indicators and soil surface characteristics allows for a more robust spatial analysis and minimises the influence of random inter-annual factors.

The practical implementation of identified productivity zones as a basis for differentiated crop management is a promising direction for further applied research. In particular, it is advisable to develop and field-test zonally differentiated sowing rates for maize seeds, application rates for mineral fertilisers, as well as the differentiated application of plant protection products, the incorporation of additional spatial data layers, and the testing of the approach in fields with other crops and under various soil and climatic conditions.

Acknowledgements

None.

Funding

None.

Conflict of Interest

None.

References

[1] Adhikari, K., Smith, D.R., Hajda, C., & Kharel, T.P. (2023). Within-field yield stability and gross margin variations across corn fields and implications for precision conservation. *Precision Agriculture*, 24, 1401-1416. doi: 10.1007/s11119-023-09995-7.

[2] Baron, F.A., Carvalho, I.R., Adorian Bandeira, W.J., Amado, T.J.C., Corassa, G.M., Fioresi, D., & Martini, R.T. (2025). Optimization of the maize hybrid plant population in a heterogeneous agricultural field. *Colloquium Agrariae*, 21(1), article number e255066. doi: 10.5747/ca.2025.v21.a540.

[3] Castaldi, F., Whalley, R.C.L., Sylvester-Bradley, R., & Rees, R.M. (2021). Spatio-temporal analysis of yield and weather data for defining site-specific crop management zones. *Precision Agriculture*, 22, 1952-1972. doi: 10.1007/s11119-021-09820-z.

[4] Chen, S., Liu, W., Feng, P., Ye, T., Ma, Y., & Zhang, Z. (2022). Improving spatial disaggregation of crop yield by incorporating machine learning with multisource data. *Remote Sensing*, 14(10), article number 2340. doi: 10.3390/rs14102340.

[5] Convention on Biological Diversity. (1992, June). Retrieved from https://www.cbd.int/convention/text/.

[6] de Oliveira Filho, M.A., Santos, A.L.C., Domingues, R.F., Melazzo, G.M., Pontes, B.S., da Silva, R.J., Hurtado, S.M.C., & Catão, H.C.R.M. (2025). Validation of management zones, variability, and spatial distribution of the physiological quality of soybean seeds. *Plants*, 14(12), article number 1856. doi: 10.3390/plants14121856.

[7] Elsharkawy, M.M., Sheta, A., D'Antonio, P., Abd-Elwahed, M.S., & Scopa, A. (2022). Tool for the establishment of agro-management zones using GIS techniques for precision farming in Egypt. *Sustainability*, 14(9), article number 5437. doi: 10.3390/su14095437.

[8] Hernández-Ochoa, I.M., Gaiser, T., Grahmann, K., Engels, A.M., & Ewert, F. (2025). Within-Field temporal and spatial variability in crop productivity for diverse crops – a 30-year model-based assessment. *Agronomy*, 15(3), article number 661. doi: 10.3390/agronomy15030661.

[9] Killeen, P., Kiringa, I., Yeap, T., & Branco, P. (2024). Corn grain yield prediction using UAV-based high spatiotemporal resolution imagery, machine learning, and spatial cross-validation. *Remote Sensing*, 16(4), article number 683. doi: 10.3390/rs16040683.

[10] Leuthold, S.J., Lavallee, J., Basso, B., Brinton, W., & Cotrufo, M.F. (2024). Shifts in controls and abundance of particulate and mineral-associated organic matter fractions among subfield yield stability zones. *SOIL*, 10, 307-319. doi: 10.5194/soil-10-307-2024.

[11] Maestrini, B., & Basso, B. (2021). Subfield crop yields and temporal stability in thousands of US Midwest fields. *Precision Agriculture*, 22, 1749-1767. doi: 10.1007/s11119-021-09810-1.

[12] Miao, L., Zou, Y., Cui, X., Kattel, G.R., Shang, Y., & Zhu, J. (2024). Predicting China's maize yield using multi-source datasets and machine learning algorithms. *Remote Sensing*, 16(13), article number 2417. doi: 10.3390/rs16132417.

[13] Mikha, M.M., Mankin, K.R., Khan, S.B., & Barnard, D.M. (2024). Precision management influences productivity and nutrients availability in dryland cropping system. *Agronomy Journal*, 116(6), 3325-3343. doi: 10.1002/agj2.21686.

[14] Narra, N., Linna, P., & Lipping, T. (2022). Calculating productivity zones of crop fields using open satellite data. In *IGARSS 2022 – 2022 IEEE international geoscience and remote sensing symposium* (pp. 6073-6076). Kuala Lumpur: IEEE. doi: 10.1109/IGARSS46834.2022.9883146.
[15] Radočaj, D., Plaščak, I., & Jurišić, M. (2025). Fusion of Sentinel-2 phenology metrics and saturation-resistant vegetation indices for improved correlation with maize yield maps. *Agronomy*, 15(6), article number 1329. doi: 10.3390/agronomy15061329.
[16] Salem, H.M., Schott, L.R., Piaskowski, J., Chapagain, A., Yost, J.L., Brooks, E., Kahl, K., & Johnson-Maynard, J. (2024). Evaluating intra-field spatial variability for nutrient management zone delineation through geospatial techniques and multivariate analysis. *Sustainability*, 16(2), article number 645. doi: 10.3390/su16020645.
[17] Sarkar, S., Osorio Leyton, G.A., Noa-Yarasca, A., Adhikari, K., Hajda, C., & Smith, D.R. (2025). Integrating remote sensing and soil features for enhanced machine learning-based corn yield prediction in the Southern US. *Sensors*, 25(2), article number 543. doi: 10.3390/s25020543.
[18] Sterle, L.G.G., & Molin, J.P. (2025). Management zones for irrigated and rainfed grain crops based on data layer integration. *Agronomy*, 15(8), article number 1864. doi: 10.3390/agronomy15081864.
[19] Tamás, A., Kovács, E., Horváth, É., Juhász, C., Radócz, L., Rátonyi, T., & Ragán, P. (2023). Assessment of NDVI dynamics of maize (*Zea mays* L.) and its relation to grain yield in a polyfactorial experiment based on remote sensing. *Agriculture*, 13(3), article number 689. doi: 10.3390/agriculture13030689.
[20] Zhu, B., Chen, S., Cao, Y., Xu, Z., Yu, Y., & Han, C. (2021). A regional maize yield hierarchical linear model combining landsat 8 vegetative indices and meteorological data. *Remote Sensing*, 13(3), article number 356. doi: 10.3390/rs13030356.

Обґрунтування виділення зон продуктивності поля за даними багаторічного моніторингу урожайності кукурудзи та супутникових показників

Леся Гарбар
Кандидат сільськогосподарських наук, доцент
Національний університет біоресурсів і природокористування України
03041, вул. Героїв Оборони, 15, м. Київ, Україна
https://orcid.org/0000-0003-4249-0434
Богдан Васьківський
Аспірант
Національний університет біоресурсів і природокористування України
03041, вул. Героїв Оборони, 15, м. Київ, Україна
https://orcid.org/0009-0003-6852-3844

Анотація. У статті наведено результати багаторічного аналізу просторової неоднорідності урожайності кукурудзи (*Zea mays* L.) на виробничому полі площею 448 га в зоні переходу між Поліссям і Лісостепом України. Дослідження проведено на основі карт урожайності за 2019-2020 та 2023-2024 роки з метою оцінки стійкості внутрішньопольових зон продуктивності та встановлення їх зв'язку із супутниковими показниками. Просторову структуру продуктивності аналізували шляхом агрегування даних yield monitor до регулярної сітки 20 × 20 м з подальшою класифікацією на три зони продуктивності. Для підтвердження агроекологічної обумовленості зон використовували багаторічні композити NDVI (Sentinel-2) та карти яскравості ґрунтової поверхні. Встановлено, що просторові межі зон низької, середньої та високої продуктивності зберігалися упродовж усього періоду досліджень, незважаючи на міжрічні коливання середнього рівня урожайності. Середні багаторічні значення становили 6,2 т/га у низькій, 9,5 т/га у середній та 12,3 т/га у високій зоні продуктивності. Коефіцієнт варіації площ зон не перевищував 11,6 %, що свідчить про їх високу просторово-часову стабільність. Кореляційний аналіз показав тісний прямий зв’язок між багаторічною картою продуктивності та середньобагаторічним NDVI (r = 0,86-0,94), а також стабільний обернений зв’язок із показниками яскравості ґрунту (r = -0,79...-0,87). Високі значення коефіцієнта детермінації (R^2 = 0,74-0,88) підтверджують, що основна частка просторової варіації урожайності зумовлена сталими ґрунтово-ландшафтними чинниками. Отримані результати доводять доцільність використання багаторічних карт урожайності у поєднанні із супутниковими індексами для виділення стабільних зон продуктивності поля. Такий підхід створює наукове підґрунтя для впровадження технологій точного землеробства та просторово диференційованого управління агроресурсами

Ключові слова: *Zea mays* L.; просторова неоднорідність поля; яскравість ґрунту; багаторічні карти урожайності; коефіцієнт детермінації; точне землеробство; management zones