International Journal of Agriculture and Biosciences 2026 15(2): 782-789.
https://doi.org/10.47278/journal.ijab/2025.198

RESEARCH ARTICLE
eISSN: 2306-3599; pISSN: 2305-6622

UAV-Based Multispectral Assessment of Soil Degradation and Grain Crop Yields in Southeastern Kazakhstan

S.B. Kenenbayev [1], V.N. Gusev [1], G.L. Yesenbayeva [2] and L.K. Tabynbayeva [1,*]

[1]Kazakh Research Institute of Agriculture and Plant Growing, Almaty region, Kazakhstan
[2]Kazakh National Agrarian Research University, Almaty, Kazakhstan
*Corresponding author: gr.sugarbeet@mail.ru

ABSTRACT

The degradation of soil fertility in Kazakhstan's arable lands, driven by prolonged anthropogenic pressures, poses a serious threat to the agro-industrial sector. This problem is especially acute in the irrigated regions of the southeast, where soil humus content has declined to critically low levels. To address this issue, the study employed multispectral imaging using unmanned aerial vehicles (UAVs) combined with the calculation of vegetation spectral indices (NDVI - Normalized Difference Vegetation Index, GNDVI - Green Normalized Difference Vegetation Index, SAVI - Soil Adjusted Vegetation Index) for monitoring winter wheat, soybean, and maize. Key soil fertility parameters, including humus horizon thickness and humus content, were correlated with vegetation indices. The efficiency of fertilizer application was evaluated through NDVI-based diagnostics, supported by direct measurements of nitrogen and chlorophyll content in plants. Furthermore, digital surface models enabled the consideration of within-field variability. The results demonstrated strong correlations between vegetation greenness indices, nutrient availability, and grain yield. NDVI proved to be a sensitive indicator of nitrogen nutrition, allowing for rapid and reliable diagnostics of plant mineral nutrition status. The integration of remote sensing techniques with ground-based observations provided an objective framework for assessing the condition of degraded soils, evaluating crop nutrient supply, and forecasting yields.

Keywords: Remote sensing, Soil degradation, Spectral index, Mineral nutrition, Winter wheat, Yield.

Article History
Article # 25-517
Received: 31-Aug-25
Revised: 04-Nov-25
Accepted: 15-Nov-25
Online First: 28-Nov-25

INTRODUCTION

Preserving the fertility of agricultural land and using it rationally is the main precondition for the stable development of the agro-industrial complex. Prolonged use of land in agricultural production causes changes in its natural properties and state. The most significant shift is the decrease in soil fertility. Fertility is one of the primary properties of soils, and its decline results from changes in all soil properties: biological, chemical, physical, hydrological, aerological, etc. (Baishanova & Kedelbaev, 2016; Emde et al., 2021; Dong et al., 2022; Deng et al., 2025). The forms and extent of changes in soil properties vary from case to case (Dunn et al., 2024; Ibraeva & Kurmanbaev, 2024). Depending on the characteristics of natural conditions and their economic use, currently about 60% of Kazakhstan's soil cover experiences varying degrees of degradation (Baishanova & Kedelbaev, 2016; Smanov et al., 2023). As a result of prolonged agricultural use, the humus content of arable soils has decreased by one-third of its initial level in non-irrigated zones and by up to 60% in irrigated conditions. Harvest removes nutrients from the soil every year, and this removal is hundreds of times greater than the input of nutrients with fertilizers. Thus, the area of soils with low humus content accounts for 63% of non-irrigated lands and almost 98% of irrigated lands (Phogat et al., 2020; Kaldybayev et al., 2021; Cheng et al., 2021). In this context, it is crucial to investigate the processes of land degradation and to develop effective strategies for mitigating the most critical issues. In addition to humus depletion (degumification), irrigated soils are increasingly affected by secondary salinization, compaction, structural deterioration, and contamination with heavy metals. These factors collectively

Cite this Article as: Kenenbayev SB, Gusev VN, Yesenbayeva GL and Tabynbayeva LK, 2026. UAV-Based multispectral assessment of soil degradation and grain crop yields in Southeastern Kazakhstan. International Journal of Agriculture and Biosciences 15(2): 782-789. https://doi.org/10.47278/journal.ijab/2025.198

A Publication of Unique Scientific Publishers

disrupt soil water–air balance and nutrient dynamics, thereby impairing plant growth and reducing crop productivity (Suska-Malawska et al., 2022; Tokbergenova et al., 2023). Addressing these challenges requires the development of innovative, cost-effective, and energy-efficient technical and technological solutions, integrating both remote sensing and ground-based monitoring approaches for sustainable land management. In the second half of the 20th century, the intensive utilization of satellite systems allowed for an increase in the diversity of data obtained in the form of space images, resulting in a more active use of multi- and hyperspectral analysis methods in various fields. The popularity of satellite data is explained by its ability to cover vast areas, a large archive, and short imaging intervals, as well as the improvement of their spatial resolution (Mikhaylenko & Timoshin, 2018; Kholodov, 2019; Jiang et al., 2025; Rigogiannis et al., 2025).

In recent years, remote sensing of the Earth (RSE) has been extensively used in agriculture to solve many practical tasks. It is applied in the monitoring of agricultural land and creating visual maps of land use with the establishment of their actual use and the identification of unused areas, including yield forecasting. The analysis of remote sensing data (climatic and geographical conditions) allows solving the main problem — forecasting the yield of agricultural crops (Bogdanova et al., 2019; Alexopoulos et al., 2023; Martynova & Kravchenko, 2023; Ferraz et al., 2024). Remote sensing makes it possible to monitor the dynamics of crop development and vegetation conditions, determine their ripening time and optimal harvest start dates, and conduct economic analysis for the minimum and maximum yield levels consistently achievable in specific conditions. Among the methods of multi- and hyperspectral analysis, vegetation spectral indices (e.g., NDVI, GNDVI, and SAVI) play a central role, as they characterize the intensity of photosynthesis and the content of chlorophyll and nitrogen in plants. Studies show that these indices make it possible to quantitatively assess the nutrient supply of plants and to predict the yield of grain crops (Kizilgeci et al., 2021; Zhang & Li, 2024). For example, the RI-NDVI index has been successfully used to assess the response of winter wheat to nitrogen (Ali et al., 2022) and the combination of NDVI and chlorophyll content indicators showed a strong correlation with the yield of durum wheat under semi-arid conditions (Kizilgeci et al., 2021). Unmanned aerial vehicles (UAVs) open up new possibilities for monitoring: they provide centimeter-level resolution and flexible timing of imaging, which is especially important for diagnosing nitrogen status and chlorophyll content in plants. The integration of UAV and satellite data significantly increases the accuracy of diagnostics and yield forecasting (Bazrafkan et al., 2025; Yang et al., 2025; Chen et al., 2025). For the conditions of Kazakhstan, the use of such modern information technologies is of particular importance. Against the background of the high degree of degradation of the region’s irrigated lands, remote sensing methods make it possible to promptly identify areas with low humus content, compaction, salinization, and other signs of degradation, and to develop targeted agrotechnical measures. Based on this, the aim of the present study was to determine, using remote sensing data, the characteristics of anthropogenic transformation, restoration, and improvement of degraded irrigated light-chestnut soils in southeastern Kazakhstan. This will make it possible to develop a methodological basis for establishing a remote monitoring system for soil degradation and grain crop productivity in the southern and southeastern regions of Kazakhstan, as well as contribute to the adaptation of agriculture to climate change and the enhancement of food security.

MATERIALS & METHODS

Aerial Survey

Aerial photography was conducted using DJI unmanned aerial vehicles (UAVs)—the Matrice 300 RTK (Real-Time Kinematic) and the Phantom 4 Multispectral—equipped with RGB (Red, Green, and Blue) and multispectral sensors. The aerial surveys were performed on June 4 and August 23, 2024, between 10:00 and 14:00 local time, under clear weather conditions and minimal cloud cover to ensure uniform surface illumination. Flights were carried out at an altitude of 100 meters, achieving a ground sample distance (GSD) of approximately 3–5cm per pixel. Real-Time Kinematic (RTK) technology was employed to enhance positional accuracy during image acquisition.

Photogrammetric Processing

Photogrammetric processing of the UAV imagery was performed using DJI Terra software, which enables automated processing and generation of high-precision georeferenced cartographic materials. The workflow included the following stages:

1. **Data Import and Preliminary Calibration**

The original RGB and multispectral images, along with RTK-corrected positional data, were imported into the software to ensure accurate georeferencing. Internal camera parameters (e.g., focal length, lens distortion) were automatically calibrated, and low-quality images were excluded to produce a consistent dataset for further analysis.

2. **Point Cloud Generation and Orthomosaic Creation**

A dense point cloud was generated automatically, followed by the production of a high-resolution orthophotomap and a digital surface model (DSM) of the study area. These outputs facilitated detailed spatial analysis of the surveyed terrain.

3. **Radiometric Correction and Vegetation Index Calculation**

Radiometric correction was applied using a calibration panel to standardize reflectance values across the dataset. Based on the processed multispectral imagery, vegetation indices—including the Normalized Difference Vegetation Index (NDVI), Green NDVI (GNDVI), and Soil-Adjusted Vegetation Index (SAVI)—were computed to assess vegetation condition and cover characteristics.

The quantitative assessment of within-field variability and nitrogen sufficiency in winter wheat crops on the experimental plot was conducted with portable photometers. In this, the leading indicator within the NDVI was the green phytomass of agricultural crops, which is determined by chlorophyll content.

The layout of the stationary experiment represents an incomplete factorial design 1/8 (4×4×4×4), including 32 variants in two replications. For convenience of presentation, the variants were coded. Each variant is designated by a four-digit number, where the order of digits corresponds to the types of fertilizers (the first — nitrogen, the second — phosphorus, the third — potassium, and the fourth — manure), and the value of each digit indicates the rate of the respective fertilizer (0, 1, 2, 3). A single rate of fertilizer was set as follows: nitrogen — 60kg ha^{-1}, phosphorus — 60kg ha^{-1}, potassium — 60kg ha^{-1}, and manure — 20 t ha^{-1}. Thus, the code 1221 corresponds to N60P120K120M20, and so on. The impact of anthropogenic factors (tillage, crops, and fertilizers) on the degree of degradation of arable soils, considering the relief, was evaluated based on fertility indicators (humus and humus horizon thickness) obtained from soil samples (Fig. 1).

A B

Fig. 1: A) map of the experimental site location; B) actual (georeferenced) locations of soil sampling points.

Statistical Analysis

All experimental data obtained from field observations, UAV-derived indices, and laboratory analyses were subjected to statistical processing to ensure accuracy and reproducibility. Descriptive statistics, including mean values, standard deviations, and coefficients of variation, were calculated for soil fertility indicators (humus content, horizon thickness), vegetation indices (NDVI, GNDVI, SAVI), nitrogen and chlorophyll concentrations, and crop yield parameters. The relationships between soil fertility parameters, vegetation indices, and yield components were evaluated using Pearson’s correlation analysis. Correlation coefficients (*r*) were computed to assess the strength and direction of associations between variables such as total nitrogen content, chlorophyll concentration, NDVI values, and grain yield. Statistical significance of correlations was determined using the *t*-test, with significance levels accepted at $P<0.05$. Confidence intervals for correlation coefficients were estimated at the 95% level. For factorial comparisons, data from the 4×4×4×4 multifactor stationary experiment were analyzed to determine the main and interaction effects of nitrogen, phosphorus, potassium, and manure application on grain yield and physiological parameters. The analysis of variance (ANOVA) was performed using a general linear model to test treatment effects, and means were compared using the least significant difference (LSD) test at $P<0.05$. Regression analyses were conducted to derive predictive models of grain yield based on nitrogen and chlorophyll contents measured during the tillering phase. Linear regression equations were fitted, and model accuracy was evaluated using the coefficient of determination (R^2) and the standard error of estimate (SEE). All statistical analyses were performed using STATISTICA 13.3 (TIBCO Software Inc.) and Microsoft Excel 2021, which were also used for graphical visualization of results, including scatter plots, trend lines, and confidence intervals.

RESULTS AND DISCUSSION

As part of this study, remote sensing was applied to create a detailed orthophoto map of the area — a photographic map showing the Earth's surface and the objects under study with precise alignment to the given coordinate system. Orthophoto maps are created based on images captured by UAVs, which are transformed from central projection to orthogonal using the orthotransformation method (Homolová et al., 2013; Pisman et al., 2015; Komarova et al., 2016; Salnikov & Tukhina, 2018). Below we juxtapose a satellite image of the area as of June 2024 (Fig. 2) and a high-resolution orthophoto map for the same period (Fig. 3).

The drawbacks of the satellite image are its insufficient resolution and interference caused by clouds, which hinder detailed analysis. The resulting orthophoto map has precise georeferencing in the EPSG (European Petroleum Survey Group) coordinate system: 32643 WGS (World Geodetic System)-84 / UTM (Universal Transverse Mercator, Northern Hemisphere, Zone 43N), and features excellent detail (3cm per pixel). This enables its overlay with other map layers and allows for comprehensive data analysis and various measurements, such as determining distances, areas, object coordinates, dimensions, and more. Orthophoto maps of the study area were utilized both as a spatial foundation for generating maps, topographic plans, and schematic representations, and as an independent analytical layer for cartographic applications, cadastral assessments, and engineering surveys. The orthophoto maps produced in this study had a scale of 1:500, ensuring high spatial precision suitable for detailed analysis.

Fig. 2: Satellite image.

Fig. 3: High-resolution orthophoto map in the coordinate system EPSG: 32643 WGS-84 / UTM zone 43N, overlaid on a satellite image.

A B

Fig. 4: Development of field crops as of: a) June 4, 2024, b) August 23, 2024.

The high-resolution orthophoto maps (Fig. 4) illustrate the dynamics of crop growth across different observation periods during the growing season—June and August 2024. Distinct changes in color reflectance were observed between the tillering and harvesting stages, transitioning from darker to lighter hues, which corresponded to variations in plant vigor and phenological development. As shown in Fig. 5, the orthophoto map obtained on June 4, 2024, revealed heterogeneity in soybean growth stages, reflecting spatial variability in early crop establishment. By contrast, the orthophoto from August 23, 2024, indicated that the entire field was in an active growth phase, with uniform vegetation cover and no visible signs of stress or degradation, confirming the overall healthy condition of the crop stand during the late-season assessment.

It has been noted in many studies that the reflectance of plants changes as they grow and develop and can characterize their physiological condition (Herrero-Huerta et al., 2020; Smith et al., 2021; Crusiol et al., 2024). In addition, a direct correlation is observed between the development of plants according to the orthophoto map (Fig. 5) and soil fertility indicators (humus horizon thickness and humus content) on these plots (Table 1). Studies on soil carbon management (Gholizadeh et al., 2018; Vaudour et al., 2019; Lal, 2020) have shown that the thickness of the humus horizon and the content of organic carbon directly affect the growth of cultivated plants, which is reflected in their spectral characteristics. Research demonstrates a direct correlation between vegetation spectral indices (NDVI, GNDVI) and data on soil humus content. Remote sensing data and orthophoto maps make it possible to visualize this relationship, including the heterogeneity of plots based on color characteristics.

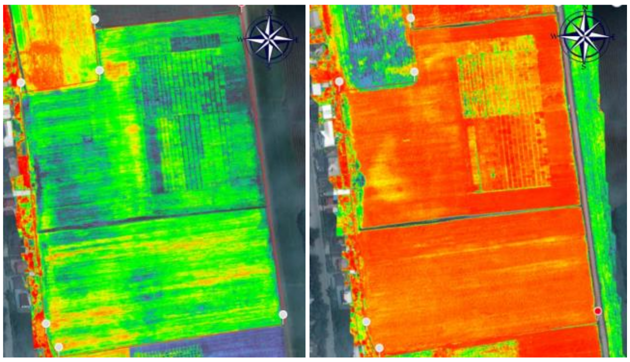
A B

Fig. 5: Development of soybean as of: a) August 23, 2024, b) June 4, 2024.

Table 1: The dependence of soil humus content on the thickness of the humus horizon in soybean crops

№	sample identifier	Geographic coordinates		Thickness, cm	Humus, %
		latitude	longitude		
1	179	43.2259008	76.6911563	30	1.67
2	119	43.2257810	76.6900919	37	1.76
3	116	43.2269819	76.6898665	50	2.57

The NDVI reflects the amount of photosynthetically active biomass and is determined by the absorption and reflection of rays in the red and near-infrared regions of the spectrum by plants. The values of the index for vegetation range from 0.20 to 0.95. The better the vegetation develops during the growing season, the higher the NDVI. Thus, the NDVI can be applied to assess plant development during the growing season. Furthermore, the NDVI can be used to monitor the stages of plant growth and development (Osipov et al., 2011; Afanas'ev, 2019; Sychev et al., 2020). Fig. 6 accurately reflects the state of the seedlings on June 4, 2024, and the stage of initial corn cob formation on August 23, 2024. The results of the soil sample analysis for fertility indicators match the level of crop development as of August 23, 2024 (Table 2). Essentially, a digital surface model is a three-dimensional depiction of surface elevations. Fig. 7 below presents the results obtained in creating the digital surface (relief) model of the experimental plot. The changes in color from light to dark demonstrate the heterogeneity of the experimental plot and an overall decrease in elevation towards the northwest. A critical condition for high and good-quality yields is ensuring that plants receive sufficient nutrients throughout the growing season. Starting from seed germination and the emergence of the primary root, winter wheat plants require phosphorus, and with the emergence of the first leaves, they start to need nitrogen. Sufficient phosphorus and nitrogen nutrition at the initial stage stimulates the growth and development of plants, improves nutrient absorption, and boosts plant growth. As can be seen from Fig. 8, nitrogen fertilizers have a decisive effect on grain yield. Phosphorus fertilizers proved to be virtually ineffective, which can be explained by the relatively high content of available phosphorus in the soil of the stationary experimental plot (40.8mg kg^{-1}) as a result of long-term and systematic application of phosphorus fertilizer. Given the significant influence of nitrogen fertilizers on the yield of winter wheat, based on research data for 2023–2025, the relationship between nitrogen and chlorophyll content in plants and grain yield was analyzed. On this basis, nitrogen supply and greenness indices were calculated (Table 3).



A B

Fig. 6: GNDVI Orthophoto Map – Dynamics of Maize Development as of: a) June 4, 2024; b) August 23, 2024.

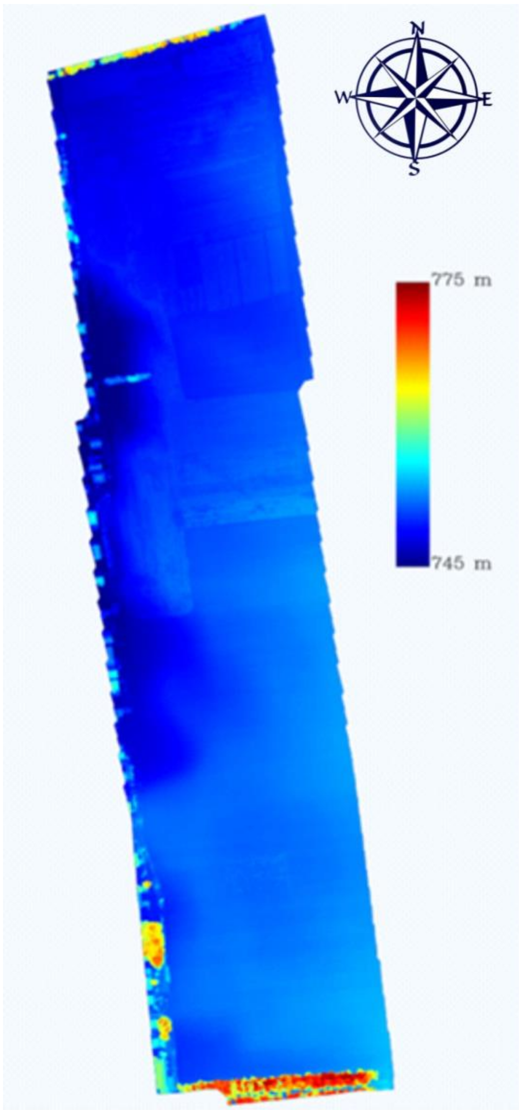


Fig. 7: Digital surface (relief) model of the experimental plot.

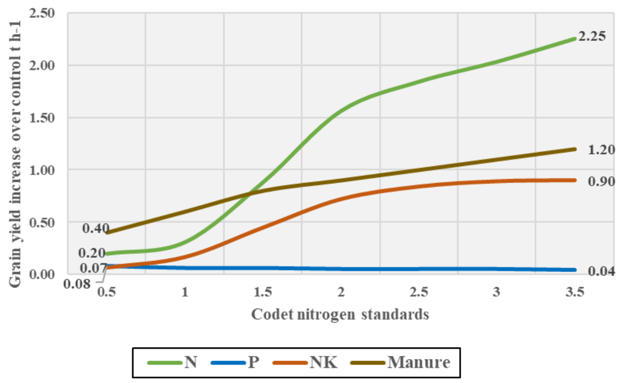


Fig. 8: The influence of fertilizers on the yield increase of winter wheat grain (in 2024–2025).

Table 2: The dependence of soil humus content on the thickness of the humus horizon in maize crops

№	sample identifier	Geographic coordinates		Thickness, cm	Humus, %
		latitude	longitude		
4	174	43.2278833	76.6908978	40	2.15
6	173	43.2282517	76.6908244	35	1.75
7	83	43.2281216	76.6891990	35	1.26
8	82	43.2285182	76.6890833	36	1.33

Table 3: Nitrogen sufficiency for winter wheat plants and greenness indices for different levels of grain yield (on average for 2023–2025)

Grain yield, t ha^{-1}	< 3.0	3.1–3.5	3.6–4.0	4.1–4.5	4.6–5.0	>5.0
Total N, %	< 2.6	2.7–3.0	3.1–3.3	3.4–3.7	3.8–4.0	>4.0
Chlorophyll, mg g^{-1}	< 1.8	1.9–2.3	2.4–2.7	2.8–3.1	3.2–3.5	>3.5

The feasibility of predicting wheat grain yield based on total nitrogen or chlorophyll content during the tillering phase—a critical developmental stage determining potential yield formation—is supported by the results presented in Figs. 9 and 10. A multifactor stationary experiment with a 4×4×4×4 factorial design comprising 32 variants and 64 plots (two replications) was conducted to compare the actual grain yield with its predicted values derived from nitrogen and chlorophyll measurements. The analysis revealed strong positive correlations between grain yield and both physiological indicators. Specifically, the correlation between grain yield and nitrogen content was r = 0.75 (n = 64, t = 8.98, P<0.05, 95% CI: 0.59–0.83), while the correlation between grain yield and chlorophyll content was r = 0.73 (n = 64, t = 8.41, P<0.05, 95% CI: 0.62–0.84). These results indicate that nitrogen and chlorophyll levels measured during the tillering stage can serve as reliable early predictors of final grain yield. Our findings are consistent with previous studies demonstrating similar relationships between spectral and biochemical indicators of plant status and yield outcomes (Filella & Peñuelas 1994; Haboudane et al., 2002; Piekarczyk et al., 2021; Kurihara et al., 2023; Nguyen et al., 2023; Jain et al., 2024). Similar relationships between vegetation indices and yield have been reported in other studies. For instance, Herrero-Huerta et al. (2020) found R^2 = 0.72 between NDVI and soybean yield using UAV multispectral data, while Jiang et al. (2025) reported R^2 = 0.78 for winter wheat when integrating UAV and satellite data. Our results align with these findings, confirming the robustness of UAV-derived indicators for early yield prediction under diverse agro-ecological conditions.

Another objective of our study was to test the possibility of determining the mineral nutrition of winter wheat plants by remote diagnostics through the photometric determination of the NDVI. Photometric diagnostics were carried out in 2023–2025 using a portable GreenSeeker sensor, which measures the NDVI index from light reflected by the leaf surface and emitted at two wavelengths (Fig. 11). The obtained spectral indices are directly dependent on the level of nitrogen sufficiency of winter wheat. With an increase in the introduced mineral nitrogen from 60 to 180kg ha^{-1}, the NDVI grew from 0.64 to 0.72. The aftereffect of 20–60t ha^{-1} of manure brought in a smaller shift — from 0.62 to 0.67. In contrast,

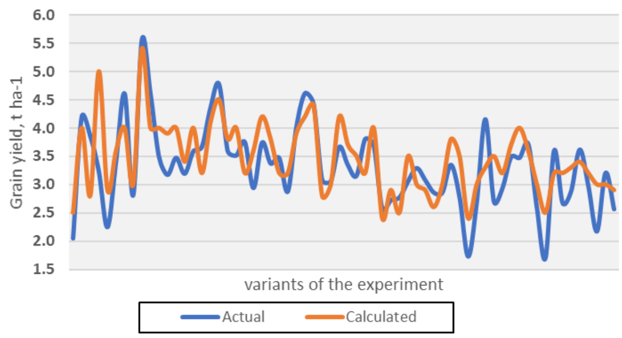


Fig. 9: Factual and estimated yields (by total N content) of wheat grain (in 2024–2025).

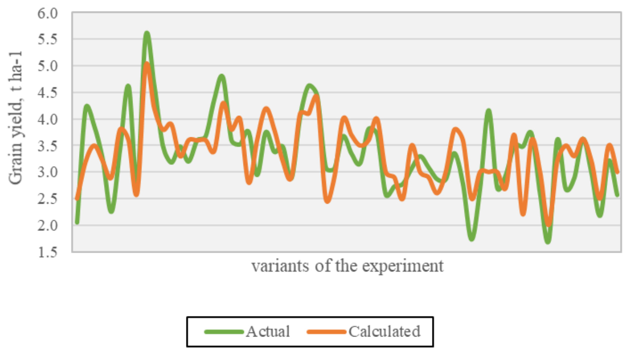


Fig. 10: Factual and estimated yields (by chlorophyll content) of wheat grain (in 2024–2025).

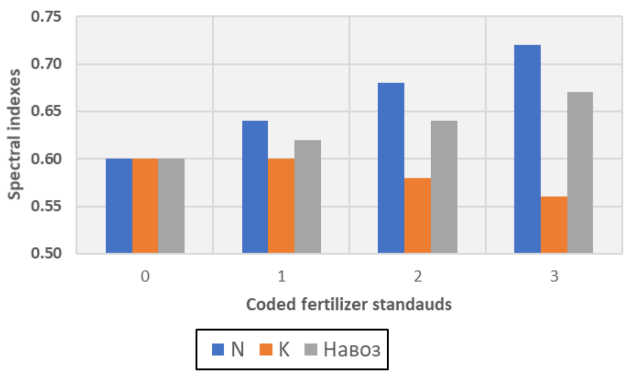


Fig. 11: Fertilizer rates and spectral indices of winter wheat at the booting stage (in 2024–2025).

potassium fertilizers had close to no effect on NDVI indicators apart from a slight downward trend at higher application rates. The provided diagnostic indicators obtained through remote sensing and traditional methods and their close association with each other and with yield, expressed by high pairwise linear correlation coefficients, prove the possibility of determining the nitrogen nutrition status of winter wheat plants based on NDVI data. The integration of UAV-based remote sensing with field nitrogen and chlorophyll assessments represents a novel methodological framework for Kazakhstan's irrigated agriculture. Unlike conventional field monitoring, this approach allows high-precision, spatially continuous assessment of soil degradation and crop stress. The study's findings can support regional precision-farming policies aimed at sustainable land use and early yield forecasting.

Conclusion

1. UAV imagery revealed changes in plant color reflectance at different growth stages and its direct relationship with soil fertility indicators.
2. The digital surface model identified heterogeneity of the plot and degradation zones, confirmed by ground-based studies.
3. Spectral indices showed a direct dependence on nitrogen supply to winter wheat: increasing nitrogen rates from 60 to 180kg ha^{-1} raised NDVI from 0.64 to 0.72; manure application (20–60t ha^{-1}) increased it from 0.62 to 0.67; potassium had almost no effect.
4. A statistical relationship was established between nitrogen and chlorophyll content in plants and grain yield; nitrogen sufficiency and greenness indices were calculated.
5. NDVI proved to be as effective as traditional methods for diagnosing nitrogen nutrition and can be used in irrigated farming to assess within-field variability and nitrogen requirements to achieve planned yields.

DECLARATIONS

Funding: Ministry of Agriculture of the Republic of Kazakhstan for 2024–2026 under project BR22885719, "Development and introduction of sustainable farming systems for profitable agricultural production under changing climate conditions for different soil and climatic zones of Kazakhstan".

Acknowledgement: We express our gratitude to Timur B. Tamenov, Engineer of the GIS Technologies and UAV Laboratory of KazNAIU, for his assistance in performing the photogrammetric processing of aerial imagery data of the experimental plot using the specialized software DJI Terra.

Conflict of Interest: The authors declare no conflict of interest.

Data Availability: All the data is available in the article.

Ethics Statement: This study did not involve humans or animals and therefore did not require official ethical approval.

Author's Contribution: Conceptualization, K.S., G.V., Y.G., T.L; Methodology, G.V., Y.G., T.L.; Investigation, K.S., G.V., Y.G.; Data Curation, G.V., Y.G.; Writing – Review & Editing, K.S., G.V., Y.G., T.L; All authors have read and approved the submitted version of the manuscript.

Generative AI Statement: The authors declare that no Gen AI/DeepSeek was used in the writing/creation of this manuscript.

Publisher's Note: All claims stated in this article are exclusively those of the authors and do not necessarily represent those of their affiliated organizations or those of the publisher, the editors, and the reviewers. Any product that may be evaluated/assessed in this article or claimed by its manufacturer is not guaranteed or endorsed by the publisher/editors.

REFERENCES

Afanas'ev, R.A. (2019). Distantsionnaya diagnostika azotnogo pitaniya rastenii s ispol'zovaniem BPLA. In V. G. Sycheva (Ed.), *Plodorodie pochv Rossii: sostoyanie i vozmozhnosti* (pp. 191–196). Moscow: VNIIA. https://doi.org/10.25680/S19948603.2020.117.08

Alexopoulos, A., Koutras, K., Ali, S.B., Puccio, S., Carella, A., Ottaviano, R. & Kalogeras, A. (2023). Complementary use of ground-based proximal sensing and airborne/spaceborne remote sensing techniques in precision agriculture: a systematic review. *Agronomy,* 13, 1942. https://doi.org/10.3390/agronomy13071942

Ali, A.M., Labuschagne, M.T., & Struwig, M. (2022). In-season estimation of wheat response to nitrogen using NDVI response index (RI-NDVI). *Precision Agriculture, 23*(6), 1764–1786. https://doi.org/10.1007/s42106-022-00207-2

Baishanova, A.E., & Kedelbaev, B.S. (2016). Problems of soil degradation: Analysis of the current state of fertility of irrigated soils in the Republic of Kazakhstan. *Scientific Review Biological Sciences, 20*, 5–13.

Bazrafkan, A., Igathinathane, C., Bandillo, N., & Flores, P. (2025). Optimizing integration techniques for UAS and satellite image data in precision agriculture: A review. *Frontiers in Remote Sensing, 6,* 1622884. https://doi.org/10.3389/frsen.2025.1622884

Bogdanova, O.V., Okmyanskaya, V.M., & Sizov, A.P. (2019). Analiz sistemy monitoringa ob"ektov osobo okhranyaemykh prirodnykh territorii na primere Tyumenskoi oblasti. *Ispol'zovanie i okhrana prirodnykh resursov v Rossii,* 3(159), 72–77. https://doi.org/10.55186/25876740_2022_6_4_6

Chen, X., Zhang, H., & Wong, C.U.I. (2025). Dynamic monitoring and precision fertilization decision system for agricultural soil nutrients using UAV remote sensing and GIS. *Agriculture, 15*(15), 1627. https://doi.org/10.3390/agriculture15151627

Cheng, M., Wang, H., Fan, J., Wang, X., Sun, X., Yang, L., Zhang, S., Xiang, Y., & Zhang, F. (2021). Crop yield and water productivity under salty water irrigation: A global meta-analysis. *Agricultural Water Management, 256,* 107105. https://doi.org/10.1016/j.agwat.2021.107105

Crusiol, L. G. T., Sibaldelli, R. N. R., Nanni, M. R., Franchini, J. C., & Farias, J. R. B. (2024). Conceitos e definições de sensoriamento remoto para monitoramento da soja (Doc. 461). Embrapa Soja. 42 c. http://www.infoteca.cnptia.embrapa.br/infoteca/handle/doc/1163887

Deng, Z., Zhu, B., Davis, S.J., Ciais, P., Guan, D., Gong, P., & Liu, Z. (2025). Global carbon emissions and decarbonization in 2024, *Nature Review Earth Environment*, 6, 231–233, https://doi.org/10.1038/s43017-025-00658-x

Dong, X., Wang, J., Zhang, X., Dang, H., Singh, B.P., Liu, X., & Sun, H. (2022). Long-term saline water irrigation decreased soil organic carbon and inorganic carbon contents. *Agricultural Water Management, 270,* 107760. https://doi.org/10.1016/j.agwat.2022.107760

Dunn, R.J.H., Blannin, J., Gobron, N., Miller, J.B. & Willett, K.M. (2024). Global climate, in: State of the Climate in 2023, *B. American Meteorological Society*, 105, S12–S155, https://doi.org/10.1175/BAMS-D-24-0116.1

Emde, D., Hannam, K. D., Most, I., Nelson, L. M., & Jones, M. D. (2021). Soil organic carbon in irrigated agricultural systems: A meta-analysis. *Global Change Biology*, *27*(16), 3898–3910. https://doi.org/10.1111/gcb.15680

Ferraz, M.A.J., Barboza, T.O.C., Arantes, P.D.S., Von Pinho, R.G., & Santos, A.F.D. (2024). Integrating satellite and uav technologies for maize plant height estimation using advanced machine learning. *AgriEngineering*, 6, 20–33. https://doi.org/10.3390/agriengineering6010002

Filella, I., & Peñuelas, J. (1994). The red edge position and shape as indicators of plant chlorophyll content, biomass, and hydric status.

International Journal of Remote Sensing, 15(7), 1459–1470. https://doi.org/10.1080/01431169408954177

Gholizadeh, A., Saberioon, M., Viscarra Rossel, R.A., & Borůvka, L. (2018). Visible, near-infrared, and mid-infrared spectral sensing for prediction of soil organic carbon content and depth of topsoil horizon. *Remote Sensing, 10*(9), 1461. https://doi.org/10.3390/rs10091461

Haboudane, D., Miller, J.R., Tremblay, N., Zarco-Tejada, P.J., & Dextraze, L. (2002). Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. *Remote Sensing of Environment, 81*(2–3), 416–426. https://doi.org/10.1016/S0034-4257(02)00018-4

Herrero-Huerta, M., Fernández-Hernández, J., Felipe-García, B., Pérez-García, J.L., de la Rocha, J., Rodríguez-Gonzálvez, P., & González-Aguilera, D. (2020). Machine learning and UAV multispectral imaging for estimating soybean yield. *Plant Methods, 16,* 78. https://doi.org/10.1186/s13007-020-00620-6

Homolová, L., Malenovský, Z., Clevers, J.G., Garcia-Santos, G., & Schaepman, M.E. (2013). Review of optical-based remote sensing for plant trait mapping. *Ecological Complexity, 15,* 1–16. https://doi.org/10.1016/j.ecocom.2013.06.003

Ibraeva, M.A., & Kurmanbaev, A.A. (2024). Current issues of soil science in Kazakhstan. *Soil Science and Agrochemistry, 20,* 94–104. https://doi.org/10.51886/1999-740X_2024_2_94

Jain, S., Sethia, D., & Tiwari, K.C. (2024). A Critical Systematic Review on Spectral-Based Soil Nutrient Prediction Using Machine Learning. *Environmental Monitoring Assessment,* 196(8):699. https://doi.org/10.1007/s10661-024-12817-6

Jiang, J., Gao, S., Li, C., Zhang, Q., & Sun, Q. (2025). Enhancing satellite monitoring of winter wheat using UAV-derived leaf chlorophyll content data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 18,* 24242–24250. https://doi.org/10.1109/JSTARS.2025.3607431

Kaldybayev, S., Erzhanova, K., Ertaeva, Z., Abdirakhymov, N., & Rustemov, B. (2021). Current state of pastures in the Republic of Kazakhstan and ways of their efficient use. *Soil Science and Agrochemistry, 10,* 14–30. https://doi.org/10.51886/1999-740X_2021_1_14

Kholodov, O.A. (2019). Kompleksnyi monitoring ispol'zovaniya zemel' sel'skokhoziaistvennogo naznacheniya v sovremennyi period. *Vestnik Volgogradskogo gosudarstvennogo universiteta. Ekonomika, 3,* 107–119. https://doi.org/10.15688/ek.jvolsu.2019.3.10

Kizilgeci, F., Albayrak, O., Ilker, E., Akan, K., Yildirim, M., & Akinci, C. (2021). Normalized difference vegetation index and chlorophyll content for precision nitrogen management in durum wheat cultivars under semi-arid conditions. *Sustainability, 13*(7), 3725. https://doi.org/10.3390/su13073725

Komarova, A.F., Zhuravleva, I.V., & Yablokov, V.M. (2016). Otkrytye multispektral'nye dannye i osnovnye metody distantsionnogo zondirovaniya v izuchenii rastitel'nogo pokrova. *Printsipy Ekologii, 10,* 40–71. https://doi.org/10.15393/j1.art.2016.4922

Kurihara, J., Nagata, T. & Tomiyama, H. (2023). Rice Yield Prediction in Different Growth Environments Using Unmanned Aerial Vehicle-Based Hyperspectral Imaging. *Remote Sensing,* 15, 2004. https://doi.org/10.3390/rs15082004

Lal, R. (2020). Managing soil carbon for climate change mitigation and adaptation in dryland agriculture. *Agronomy, 10*(3), 405. https://doi.org/10.3390/agronomy10030405

Martynova, N.G., & Kravchenko, V.G. (2023). Monitoring sel'skokhoziaistvennykh zemel' po dannym distantsionnogo zondirovaniya. *International Agricultural Journal, (1),* 69–86. https://doi.org/10.55186/25876740_2023_7_1_7

Mikhaylenko, I.M., & Timoshin, V.N. (2018). Mathematical modeling and measurement of the chemical state of the soil environment based on remote sensing data. *International Research Journal, 9*(75), Part 2, 26–37. https://doi.org/10.23670/IRJ.2018.75.9.029

Nguyen, C., Sagan, V., Bhadra, S. & Moose, S. (2023). UAV Multisensory Data Fusion and Multi-Task Deep Learning for High-Throughput Maize Phenotyping. *Sensors*, 23, 1827. https://doi.org/10.3390/s23041827

Osipov, Y.F., Ivanitskii, Y.V., Shirinyan, M. K., Afanas'ev, R.A., & Galitskii, V.V. (2011). Ispol'zovanie pribora N-tester "Yara" dlya diagnostiki azotnogo pitaniya ozimoi pshenitsy. *Plodorodie, 21,* 26–29.

Phogat, V., Mallants, D., Cox, J.W., Šimůnek, J., Oliver, D.P., Pitt, T., & Petrie, P.R. (2020). Impact of long-term recycled water irrigation on crop yield and soil chemical properties. *Agricultural Water Management, 237,* 106167. https://doi.org/10.1016/j.agwat.2020.106167

Piekarczyk, J., Kołodziejczyk, M., Kupidura, P., & Kozłowski, R. (2021). Estimation of nitrogen content in winter wheat using remote sensing data. *Remote Sensing, 13*(7), 1349. https://doi.org/10.3390/rs13071349

Pisman, T.I., Botvich, I.Y., & Sidko, A.F. (2015). Assessment of agroecosystem productivity based on satellite data and a mathematical model. *Journal of Siberian Federal University: Engineering & Technology, 1*(8), 133–140. https://elib.sfu-kras.ru/handle/2311/16715

Rigogiannis, N., Almpanopoulos, I., Kanimas, I., Fragkos, A., Chempas, G., Papanikolaou, N., & Agelidis, V.G. (2025). Nanosatellites in Precision Agriculture—Comparison with Drone-Based Applications and Improved Power Distribution Unit Design. *IEEE Transactions on AgriFood Electronics*, *3*(2), 336–347. https://doi.org/10.1109/TAFE.2025.3598691

Salnikov, S.G., & Tukhina, N.Y. (2018). Geoinformatsionnye sistemy kak bazovaya sistema informatsionnogo obespecheniya sel'skogo khozyaistva. *Vestnik Moskovskogo Gumanitarno-Ekonomicheskogo Instituta, 4,* 100–103. https://doi.org/10.52575/2712-7443-2022-46-4-539

Smanov, Z.M., Suleimenova, A.I., Poshanov, M.N., Duisekov, S.N., & Vyrahmanova, A.S. (2023). Current reclamation state of irrigated soils and the methodology of their study on the example of SPC "Asia Agro Group." *Soil Science and Agrochemistry, (1),* 15–35. https://doi.org/10.51886/1999-740X_2023_1_15

Smith, S.D., Prasad, P.V.V., Reddy, K.R., Marek, T., Colaizzi, P.D., & Xue, Q. (2021). Multispectral reflectance-based remote sensing for evaluating soybean growth and yield under excess water stress. *Remote Sensing, 13*(15), 2911. https://doi.org/10.3390/rs13152911

Suska-Malawska, M., Vyrakhamanova, A., Ibraeva, M., Poshanov, M., Sulwiński, M., Toderich, K., & Mętrak, M. (2022). Spatial and in-depth distribution of soil salinity and heavy metals (Pb, Zn, Cd, Ni, Cu) in arable irrigated soils in southern Kazakhstan. *Agronomy, 12*(5), 1207. https://doi.org/10.3390/agronomy12051207

Sychev, V.G., Afanas'ev, R.A., & Kirsanov, G.A. (2020). Vozmozhnosti distantsionnoi diagnostiki mineral'nogo pitaniya rastenii. *Plodorodie, (2),* 13–17. https://doi.org/10.25680/S19948603.2020.113.04

Tokbergenova, A.A., Zulpykharov, K.B., Kaliyeva, D.M., & Essanbekov, M.Y. (2023). Assessment of the current soil-reclamation state of the soils of Myrzashol in the Kazakhstan part (the Hungry Steppe). *Polish Journal of Environmental Studies, 32*(1), 789–805. https://doi.org/10.15244/pjoes/155087

Vaudour, E., Gomez, C., Loiseau, T., & Baghdadi, N. (2019). Monitoring agricultural practices from space to assess soil organic carbon content: A review. *Agronomy for Sustainable Development, 39*(1), 16. https://doi.org/10.1007/s13593-019-0561-7

Yang, X., Chen, J., Lu, X., Liu, H., Liu, Y., Bai, X., Qian, L., & Zhang, Z. (2025). Advances in UAV remote sensing for monitoring crop water and nutrient status. *Plants, 14*(16), 2544. https://doi.org/10.3390/plants14162544

Zhang, W., & Li, Y. (2024). A spatio-temporal-spectral fusion framework for downscaling sentinel-2 images using uav images. *International Journal Remote Sensing*, 46, 1257–1278. https://doi.org/10.1080/01431161.2024.2429781