AUTOMATION AND COMPUTER-INTEGRATED TECHNOLOGIES

UDC 528.854:681.5.015.42(045)
DOI:10.18372/1990-5548.86.20561

[1]**V. M. Sineglazov,**
[2]**R. S. Koniushenko**

FEATURE EXTRACTION FOR MULTISPECTRAL ANALYSIS OF CEREAL CROPS USING OPTIMIZED COMPUTER VISION PIPELINES

Aviation Computer-Integrated Complexes Department, Faculty of Air Navigation Electronics and Telecommunications, State University "Kyiv Aviation Institute", Kyiv, Ukraine
E-mails: [1]svm@nau.edu.ua ORCID 0000-0002-3297-9060, [2]4064821@stud.nau.edu.ua

Abstract*—The article presents the results of a study aimed at improving the stability, reproducibility, and structural consistency of computer vision pipelines for multispectral unmanned aerial vehicles imagery of winter wheat canopies. A new adaptive preprocessing model is introduced, incorporating illumination normalization based on a modified Retinex/MSRCR algorithm, entropy-regulated spatial-spectral filtering for noise suppression, and instability-driven spectral feature fusion to obtain stable multispectral descriptors. The model is formulated as a multi-objective preprocessing framework, jointly optimizing illumination invariance, noise robustness, structural preservation, and information richness. Experiments conducted on the open-access unmanned aerial vehicles dataset of nine winter-wheat fields (Switzerland) demonstrated a reduction of the coefficient of variation to 0.12 and RMSE to 0.089, together with improvements in structural similarity (SSIM = 0.923) and spectral entropy (H = 5.9), significantly outperforming classical normalization methods. The results confirm the effectiveness of the proposed approach in mitigating illumination heterogeneity and sensor-induced distortions, ensuring stable and phenologically consistent feature extraction. The developed framework can be integrated into computer-integrated and robotic precision-farming systems to enhance the reliability of automated monitoring and decision-support processes in winter-wheat production.*

Keywords—Multispectral analysis; computer vision; unmanned aerial vehicle; precision farming; feature stabilization.

I. INTRODUCTION

Modern grain production, primarily the cultivation of wheat, barley and oats, takes place under the growing pressure of climate change and the associated phytosanitary risks [1]. In the early stages of growth, these crops are characterized by uniformity of seedlings, density of plants in a row and uniform light green color of the leaf surface; In the phases of tillering and exit into the tube, there is a closure of rows, an increase in the intensity of green color, an increase in height and the formation of a more complex geometric structure of sowing. At later stages – earing and grain filling – the signs of the spatial organization of the above-ground mass dominate: the alignment of the ears in height, the uniformity of color, the stability of the cover structure. Climatic anomalies - heat waves, droughts, excessive precipitation, storm and wind events – change the physiological state of plants, which is manifested in spectral and visual signs: local or continuous yellowing, wilting, color heterogeneity, rupture of row geometry, the appearance of gaps. Weeds form a mosaic cover with a shade of green different from cultivated plants, a different type of leaf surface and chaotic geometry, disrupting the regularity of the sowing structure. Pests and pathogens cause discoloration of leaves, the appearance of spots, necrotic areas, deformation of individual plants and spotting of the cover, which changes both the color and the textural and geometric characteristics of the field. According to the IPPC, climate change leads to changes in the habitats and abundance of pests, an increase in the number of generations during the season, the emergence of new crop-pest combinations and an increased risk of invasive species, which makes the timely detection of such visual and spectral signs critical for crop conservation [1].

II. REVIEW OF LATEST ARTICLES

Recent research in computer vision for cereal-crop imaging has evolved from ad-hoc processing pipelines toward systematic and operational frameworks that integrate multispectral and temporal information with machine-learning feature extractors. These developments reflect a growing emphasis on preprocessing robustness – adderssing illumination variability, sensor noise, and background clutter, which remain critical obstacles in real-world field environments.

At the landscape scale, Zhang et al. [1] offer a valuable and systematic synthesis of crop-specific land-cover products, with particular strengths in detailing EO preprocessing strategies such as radiometric correction, atmospheric normalization, and terrain adjustment. Their review of more than sixty operational and archival datasets convincingly demonstrates that disciplined preprocessing – especially consistent atmospheric correction, cloud masking, and temporal reflectance normalization – is fundamental to achieving reproducible crop-type mapping. This rigor is an important contribution, as it helps preserve the physical meaning of phenology-aware features derived from Landsat and Sentinel imagery.

However, despite its breadth, the review remains oriented toward satellite-scale assumptions: it presumes relatively homogeneous illumination, stable atmospheric conditions, and limited fine-grained noise. These assumptions become limiting when preprocessing pipelines are transferred to UAV-based or plot-scale contexts, where illumination heterogeneity, micro-topographic shading, and sensor-induced variability are far more pronounced. As a result, many of the surveyed approaches lack practical robustness when applied to high-resolution, low-altitude imaging.

This gap – strong methodological discipline at the satellite level but insufficient adaptability at the UAV scale – highlights the need for preprocessing frameworks that explicitly account for local illumination variability and noise structures. Against this background, the present work positions itself as an effort to bridge this methodological discontinuity by developing preprocessing techniques tailored to the more challenging and heterogeneous conditions of close-range multispectral crop analysis.

From the perspective of object-level imagery, the review by Velesaca et al. [2] makes a strong contribution by providing a structured taxonomy of computer-vision pipelines for food-grain classification and by clearly distinguishing the functional roles of acquisition, preprocessing, segmentation, and classification. Their strengths lie in demonstrating how illumination normalization and color calibration critically affect the stability of RGB-based features, while multispectral and hyperspectral data significantly enhance class separability. Yet, the authors also identify several systemic limitations in the field: the lack of standardized benchmarks, the low reproducibility of handcrafted features, and persistent vulnerability to uncontrolled illumination and sensor drift. These weaknesses underscore a broader methodological issue – the absence of preprocessing frameworks that can consistently stabilize features under diverse environmental conditions. As Velesaca et al. conclude, illumination and spectral balancing remain the major bottlenecks for reproducible feature extraction, which further reinforces the relevance of developing adaptive and robust preprocessing models such as the one proposed in the present study.

At the regional scale, Halder et al. [3] present a technically strong crop-mapping framework that leverages complementary Sentinel-1 SAR and Sentinel-2 multispectral time series alongside gradient-boosting and BiLSTM architectures. A key advantage of their approach is the effective integration of heterogeneous sensors, demonstrating that cross-sensor normalization and temporal smoothing substantially improve classification stability and allow the model to surpass single-sensor baselines by 2–3%. Their preprocessing scheme – with gap filling and percentile-based normalization – illustrates a well-designed strategy for mitigating noise, atmospheric variability, and illumination fluctuations.

However, the framework exhibits notable limitations: it is heavily dependent on dense temporal stacks, requires substantial computational resources, and remains optimized for large-area satellite applications rather than fine-grained, near-real-time field scenarios. These constraints reduce its practicality for UAV-level monitoring, where data volumes are smaller but illumination heterogeneity and sensor noise are more pronounced, and where lightweight preprocessing is essential.

Taken together, the strengths and weaknesses highlighted by Halder et al. reinforce a broader insight shared across regional-scale studies: while cross-sensor normalization and temporal filtering are powerful, they remain computationally burdensome and insufficiently adaptable for high-resolution, close-range imaging. This further motivates the development of efficient, illumination-aware preprocessing methods – as pursued in the present work – to address the gaps left by satellite-oriented frameworks.

Within the domain of in-field plant health monitoring, Ashraf et al. [4] present a lightweight CNN architecture that clearly demonstrates the benefits of targeted preprocessing for stabilizing features in uncontrolled field imagery. Their approach shows a notable strength: denoising, contrast normalization, and background suppression substantially enhance robustness, allowing the model to reach 93% accuracy despite illumination variability. This highlights the importance of preprocessing as a decisive factor, especially when working with heterogeneous, high-resolution mobile imagery.

At the same time, the study exposes structural weaknesses typical of lightweight, dataset-specific CNNs. The model is tested on a relatively small and carefully curated in-field dataset, raising concerns about generalization to broader environmental conditions, sensor types, and disease manifestations. Its reliance on manual annotation and controlled sampling also limits scalability, while the absence of cross-condition validation constrains its applicability to more complex field environments.

Overall, the work by Ashraf et al. underscores a recurring pattern across in-field plant monitoring studies: preprocessing can significantly stabilize performance, but existing pipelines remain highly dependent on dataset curation and lack mechanisms to handle illumination heterogeneity and sensor-induced variability in a systematic way. These limitations reinforce the relevance of the present study, which addresses preprocessing consistency more explicitly and seeks methods that retain stability without requiring highly controlled data collection.

Two UAV-based studies advance the discussion on preprocessing and feature engineering by demonstrating both the potential and the persistent limitations of current approaches. Zhang et al. [5] make a notable contribution by proposing local optimized features (LOFs), a targeted strategy designed to mitigate illumination instability and soil-background interference. A key strength of their work is the clear empirical gain – raising pre-winter seedling classification accuracy from 0.86 to 0.99 – showing that locally adaptive descriptors can substantially outperform conventional mean vegetation indices. However, the method remains dependent on manually tuned LOF parameters and presupposes accurate canopy delineation, which limits its scalability and reduces its robustness when field conditions deviate from controlled assumptions.

In parallel, Zhou et al. [6] present a well-structured phenotyping pipeline emphasizing rigorous preprocessing: linear-regression–based color calibration, ExG segmentation, and refined anisotropic diffusion filtering. The strength of this approach lies in its high reproducibility and strong agreement with ground-truth measurements (r = 0.942), along with reduced geometric distortions. Yet, the reliance on calibrated camera settings and strict flight-altitude control constrains broader applicability, particularly in operational scenarios where UAV configurations and illumination vary.

Together, these studies illustrate that while sophisticated preprocessing and feature design can dramatically improve classification accuracy, existing methods still struggle with adaptability, parameter dependence, and environmental variability. This gap underscores the need for approaches that retain the strengths of UAV-based precision (fine-scale descriptors and high-throughput acquisition) while reducing sensitivity to calibration constraints and manual tuning – thereby situating the relevance of the present work in addressing these unresolved challenges.

Sandoval-Pillajo et al. [7] provide one of the most comprehensive syntheses of UAV-based weed detection, reviewing 77 studies and offering a strong evaluation of the current algorithmic landscape. A key strength of their work is the clear identification of where modern deep architectures – YOLO, U-Net, Mask R-CNN, and emerging Transformer-based detectors – remain effective and where they systematically fail. Their analysis shows that regardless of network complexity, preprocessing limitations such as RGB ambiguity, occlusion, and inconsistent illumination still undermine model generalization. This critical insight exposes a structural weakness in the field: advances in detection architectures cannot compensate for unstable input features. The authors argue that reliable weed mapping increasingly depends on multisensor integration and illumination-aware normalization, positioning preprocessing – not model depth – as the decisive factor in robustness. This conclusion aligns with trends across other UAV-based studies and further underscores the relevance of developing adaptive, illumination-stable preprocessing methods such as those pursued in the present work.

In summary, the reviewed literature highlights that existing preprocessing methods – ranging from simple normalization and filtering to complex multisensor harmonization – have substantially improved crop monitoring but still suffer from high sensitivity to illumination, sensor noise, and spatial heterogeneity. Many approaches depend on handcrafted tuning or computationally intensive normalization, reducing scalability and real-time applicability for UAV-based field operations.

Therefore, a critical research gap remains: the absence of a unified, adaptive preprocessing approach that dynamically stabilizes multispectral descriptors of cereal crops under variable field conditions. This study addresses that gap by developing a hybrid preprocessing–feature stabilization method that integrates illumination normalization, adaptive noise suppression, and spectral fusion within a single, energy-efficient framework for resilient agricultural computer vision.

III. PROBLEM STATEMENT

In modern precision agriculture, multispectral imaging has become one of the key tools for assessing crop condition, detecting early signs of stress, and supporting automated decision-making in large-scale production systems. However, despite significant progress in sensor technologies and machine-learning methods, the reliability of image-based analytics in real field conditions remains limited. Variations in natural illumination, atmospheric influences, and sensor noise lead to instability of spectral features and reduce the reproducibility of subsequent classification or monitoring results. As agricultural robots and UAV platforms increasingly rely on fully automated perception pipelines, the development of robust preprocessing methods capable of stabilizing multispectral data under heterogeneous environmental conditions becomes especially relevant. This work addresses this challenge by proposing an optimized preprocessing – feature stabilization model aimed at improving the consistency and informativeness of multispectral descriptors for cereal-crop analysis. Modern methods of computer vision in the agricultural sector are actively used to analyze multispectral images of crops, but their effectiveness is significantly limited by the instability of lighting, atmospheric disturbances and sensor noise in the field. These factors reduce the accuracy of trait isolation, lead to spectral distortion and impair data consistency between channels, which directly affects the quality of crop classification, assessment of their condition and phenological monitoring. As noted by Zhang et al. [1] and Velesaca et al. [2], building scalable and resilient analysis systems is only possible with robust preprocessing that takes into account lighting variations and noise effects even before the machine learning stages.

Despite significant advances in deep learning-based segmentation and classification, the problem of stable isolation of traits from multispectral images of cereals remains open. The lack of adaptive pre-treatment models capable of compensating for lighting changes and noise artifacts without losing textural information limits the accuracy of automated monitoring systems in precision farming. This necessitates the development of optimized computer vision pipelines that ensure the stability of features regardless of external conditions and can be integrated into robotic agricultural monitoring platforms.

To formalize the challenge addressed in this study, consider a multispectral UAV-based imaging system that acquires a sequence of images

$$I = \{I_1, I_2, \ldots, I_n\},\ I_k : \Omega \to R^C, \tag{1}$$

where $\Omega \to R^C$ denotes the image domain and C the number of spectral channels. For each pixel (i, j), the observed vector

$$x_{ij} = I_k(i, j), \tag{2}$$

results from the interaction between the true surface reflectance s_{ij} and several sources of variability, including illumination heterogeneity L, sensor noise N, and background interference B:

$$x_{ij} = f(s_{ij}, L, N, B). \tag{3}$$

The aim of preprocessing is to obtain a normalized descriptor

$$\hat{s}_{ij} = g(x_{ij}), \tag{4}$$

where the transformation gproduces feature representations that remain consistent under changing illumination, exhibit minimal noise-induced variance, and preserve structures necessary for agronomic interpretation. Ideally, this mapping satisfies illumination invariance, expressed as

$$g\left(f\left(s_{ij}, L_1, N_1, B_1\right)\right) \approx g\left(f\left(s_{ij}, L_2, N_2, B_2\right)\right), \tag{5}$$

ensures noise robustness by minimizing the variance of the transformed signal,

$$\mathrm{Var}\left(g\left(x_{ij}\right)\right) \to \min, \tag{6}$$

and maintains structural fidelity,

$$d\left(g(s_a), g(s_b)\right) \propto d\left(s_a, s_b\right), \tag{7}$$

so that meaningful spectral and spatial differences between crop states remain identifiable.

In compact form, the preprocessing problem can be expressed as an optimization task:

$$\mathrm{g}* = \arg\min_{\mathrm{g}\in\mathcal{G}}\left[\alpha\mathcal{L}_{\mathrm{illum}}(\mathrm{g}) + \beta\mathcal{L}_{\mathrm{noise}}(\mathrm{g}) + \gamma\mathcal{L}_{\mathrm{structure}}(\mathrm{g})\right], \tag{8}$$

where α, β, γ regulate the balance between illumination compensation, noise suppression, and structure preservation. This formulation reflects the core difficulty inherent to UAV-based crop imaging: the same physical surface can produce drastically different measurements depending on flight geometry, sunlight dynamics, and sensor artefacts, whereas downstream feature extractors expect stable inputs.

In the context of winter wheat analysis, reliable early-season monitoring depends on the stability of several groups of spectral and structural descriptors. Vegetation indices such as NDVI, GNDVI, EVI, RVI, and red-edge derivatives (e.g., NDRE or chlorophyll indices) provide valuable information about chlorophyll concentration, nitrogen uptake and biomass development. However, these indices are highly sensitive to illumination fluctuations, shading effects and exposure variability, which often arise during low-altitude UAV flights.

Band-ratio features, constructed as normalized relationships between spectral channels, partially compensate for brightness variations but remain vulnerable to sensor noise, compression artefacts and heterogeneous soil backgrounds. Color-space descriptors, including CIELab components, green-red excess measures, or HSV-derived contrasts, are important for canopy-soil separation and for characterizing early seedling vigor. Nevertheless, they degrade significantly under inconsistent white balance, rolling-shutter distortions or automatic gain adjustments typical of UAV cameras.

Structural information extracted from texture measurements, such as GLCM-derived contrast, homogeneity, entropy or gradient-based statistics, captures fine-scale canopy architecture – tiller density, leaf orientation patterns, planting uniformity. These features, however, are extremely sensitive to illumination directionality, shadows cast by micro-relief, and altitude-related changes in spatial resolution. Likewise, morphological descriptors such as canopy coverage or seedling density are informative but depend strongly on the stability of segmentation thresholds, which themselves fluctuate under variable lighting.

Across all these feature categories, a consistent pattern emerges: descriptors that are agronomically meaningful under controlled illumination become unstable and difficult to reproduce in real UAV conditions. Illumination heterogeneity, sensor-induced distortions and background interference propagate into every type of feature, from spectral ratios to structural measures. Consequently, the reliability of wheat monitoring depends primarily on the consistency of preprocessing rather than on the complexity of subsequent machine-learning models.

Taken together, these observations lead to the central motivation of this study: the need to design a preprocessing transformation g^* capable of producing illumination-normalized, noise-suppressed and structurally consistent descriptors. Achieving such stability is essential for ensuring that multispectral and RGB features remain comparable across flights, dates, sensors and environmental conditions, thereby enabling robust UAV-based wheat analysis.

The objective of this study is to develop and validate an adaptive preprocessing and feature stabilization model for multispectral UAV imagery of winter wheat canopies within an explicitly multi-criteria framework, ensuring stability, structural consistency, and information richness of extracted features under variable illumination and noise conditions. Specifically, the research seeks to:

1) Formulate the preprocessing pipeline as a genuinely multi-objective problem in which illumination normalization (MSRCR-based), noise suppression (NoiseNet/AEF), and spectral feature fusion (StabiNet) are jointly tuned with respect to a vector of quality criteria rather than a single aggregated loss.

2) Quantitatively evaluate the effect of each processing stage on descriptor stability and structural fidelity using a set of complementary metrics – coefficient of variation (CV) and entropy (H) for feature stability, structural similarity index (SSIM) for spatial–spectral consistency, and root mean square error (RMSE) for robustness to noise – treating each metric as a separate optimization objective.

3) Analyse the trade-offs between these criteria and establish functional relationships between the adaptive parameters of the model and the metric vector {CV, H, SSIM, RMSE}, demonstrating how configurations on the Pareto front correspond to practically useful compromises between stability, information content, structural preservation, and noise resistance.

The expected outcome is a validated preprocessing–stabilization framework whose performance is characterized not by a single scalar score, but by coordinated improvements across CV, H, SSIM, and RMSE, confirming that the method provides consistent and reproducible feature extraction for precision agriculture under diverse environmental and sensor conditions.

IV. Proposed Method

To ensure practically relevant and reproducible multispectral feature extraction in precision agriculture, the proposed method is exclusively developed and evaluated on UAV-based multispectral imagery of winter wheat fields. Winter wheat was selected as the core study crop due to its global importance as a staple cereal, well-documented phenology, and characteristic canopy structure, which includes dense row-based stands, rapid changes in leaf area index, and pronounced textural and color transitions between tillering, stem elongation, heading, and grain filling stages. These properties make winter wheat particularly sensitive to variations in illumination, sensor noise, and viewing geometry, causing substantial instability in spectral-spatial descriptors if preprocessing is inadequate. Focusing on this crop therefore provides a stringent and agriculturally meaningful testbed for assessing feature stability, structural consistency, and information richness under real field conditions.

Therefore, it is necessary to develop a robust computer vision method that ensures feature stability regardless of environmental conditions. The experimental setup was designed specifically to ensure stable isolation of multispectral features from UAV-based imagery of winter wheat fields for subsequent integration into automated monitoring and control systems in precision agriculture, including autonomous ground platforms, unmanned aerial vehicles, and robotic surveillance systems.

The proposed method consists of a hybrid algorithmic pipeline that integrates three main stages:

1) *Illumination Normalization* using a modified Multispectral Retinex with Color Restoration (MSRCR) to correct uneven lighting.

2) *Noise Suppression* via an adaptive spatial-spectral filtering algorithm that combines median and Gaussian filters with entropy-based adjustment of smoothing intensity.

3) *Feature Stabilization and Adaptive Fusion*, where spectral feature vectors are normalized and merged according to weighting coefficients derived from a minimization of instability functionals.

Together, these algorithms form a composite method aimed at stabilizing multispectral descriptors prior to classification or learning stages. In this study, the workflow is applied specifically to winter wheat canopies, where spectral-spatial descriptors are highly sensitive to illumination variability and sensor noise due to dense row structure, rapid phenological transitions, and fine-scale textural heterogeneity.

The second stage of the pipeline implements NoiseNet, a lightweight convolutional denoising network inspired by DnCNN architecture but adapted for multispectral UAV data. It consists of six convolutional layers (3×3 kernels, ReLU activation) followed by batch normalization and residual connections to preserve spatial detail. The network is trained to minimize the Mean Squared Error (MSE) between noisy and clean multispectral patches simulated under Gaussian, Poisson, and speckle noise models.

For field deployment where full training is infeasible, a hybrid variant – Adaptive Entropy Filter (AEF) – is used. AEF combines the output of NoiseNet with an adaptive spatial–spectral filter whose smoothing coefficient is dynamically adjusted by local entropy estimation. This ensures effective suppression of both high-frequency and structured sensor noise without destroying spectral relationships.

In the third stage, Feature Stabilization is performed using a neural spectral fusion block named StabiNet. StabiNet applies a fully connected layer followed by a Softmax-based weighting mechanism to fuse channel-wise normalized features. Weight coefficients are computed by minimizing a differentiable instability loss function $L_{\text{stab}} = \| F_t - F_{t-1} \|^2 + \lambda \, \mathrm{Var}(F)$, which penalizes temporal and spatial fluctuations of feature maps. This produces stable multispectral descriptors suitable for subsequent classification or segmentation tasks.

The combined processing chain – MSRCR + NoiseNet/AEF + StabiNet – constitutes a complete hybrid preprocessing-stabilization framework optimized for UAV-based multispectral analysis of winter wheat, ensuring stable, structurally consistent, and information-rich features under real field conditions.

The model was developed using the Python 3.11 programming language, which provides flexible integration of signal processing and machine learning methods. For the implementation of processing and analysis modules, OpenCV, scikit-image, NumPy, SciPy and TensorFlow/Keras libraries were used, ensuring high-performance computation on both CPU and GPU. The neural modules (NoiseNet and StabiNet) were implemented in TensorFlow / Keras, while hybrid filtering and entropy adjustment were realized in NumPy and OpenCV. The Visual Studio Code environment was used for code development and debugging, and GitHub Actions supported version control and reproducibility of experiments, enabling automated testing of algorithmic stability.

The experimental part of this study was conducted using the open-access "UAV dataset of nine wheat fields in Switzerland with raw, processed and meta data" [9], which contains UAV imagery and comprehensive field-level metadata for European winter wheat production. The dataset was used as the primary source of structured information, including georeferenced field boundaries, handheld frame annotations across multiple acquisition dates (March–April 2020), crop management logs, and detailed records of sensor parameters and flight configurations. These metadata files describe multiple winter-wheat fields located in distinct Swiss agricultural regions (such as Villars-le-G and Volken), covering early and mid-season phenological stages relevant for multispectral feature analysis. The dataset also provides calibration data, treatment maps, and per-field management histories, enabling realistic reconstruction of illumination variability, canopy structure, and acquisition geometry. This makes the dataset a reliable and domain-appropriate foundation for evaluating preprocessing robustness and feature stability in UAV-based analysis of winter wheat canopies.

The developed model has a modular three-level architecture specifically oriented toward multispectral analysis of winter wheat fields within computer-integrated agricultural monitoring systems. The pipeline includes three core steps: illumination normalization (Retinex/MSRCR), noise suppression (adaptive median + Gaussian filtering), and feature stabilization followed by adaptive fusion. The data originate from UAV-based acquisitions of European winter wheat canopies, complemented by synthetically generated variations in illumination and noise to reproduce realistic field conditions. The performance of the model is evaluated using CV, entropy, SSIM, and RMSE metrics, and the resulting stabilized features are further applied to tasks such as semantic segmentation, phenotypic structure analysis, and within-field variability assessment (Fig. 1).

The Illumination Normalization Unit performs local brightness correction using an advanced Multispectral Retinex with Color Restoration (MSRCR) model adapted to multispectral bands of winter wheat canopy imagery. Under field conditions, winter wheat exhibits pronounced illumination variability caused by row structure, leaf angle distribution, and shadowing effects; therefore, MSRCR is applied to stabilize the spectral response prior to further processing. For each pixel, the intensity is normalized according to:

$$I'_{\lambda}(x,y) = \log\left(I_{\lambda}(x,y)\right) - \log\left(G_{\sigma_{\lambda}} \cdot I_{\lambda}(x,y)\right), \quad (9)$$

where $I_{\lambda}(x,y)$ is the initial value of intensity in the spectral channel λ, a $G_{\sigma_{\lambda}}$ – gaussian filter with anti-aliasing parameter σ_{λ}. This ensures the elimination of lighting irregularities and shadows, which are especially relevant for low UAV flight altitudes. The noise suppression unit implements a combined spatial-spectral filtering algorithm designed specifically to address the characteristic noise patterns observed in UAV imagery of winter wheat canopies, where fine-scale leaf structure and row-induced shading often amplify high-frequency distortions. First, adaptive median filtering is applied to reduce impulse noise, followed by regularized anti-aliasing using a weighted Gaussian function. Unlike classical fixed-parameter methods, the proposed scheme employs a dynamic filtering coefficient α(λ), which depends on the local entropy of the spectral fragment:

$$\alpha(\lambda) = \frac{1}{1 + e^{-\beta(H_{\lambda} - H_0)}}, \quad (10)$$

where H_{λ} is the local entropy of the spectral channel; H_0 is the signal stability threshold; β is the steepness parameter. This approach allows to adaptively adjust the anti-aliasing force depending on the textural characteristics of the scene.

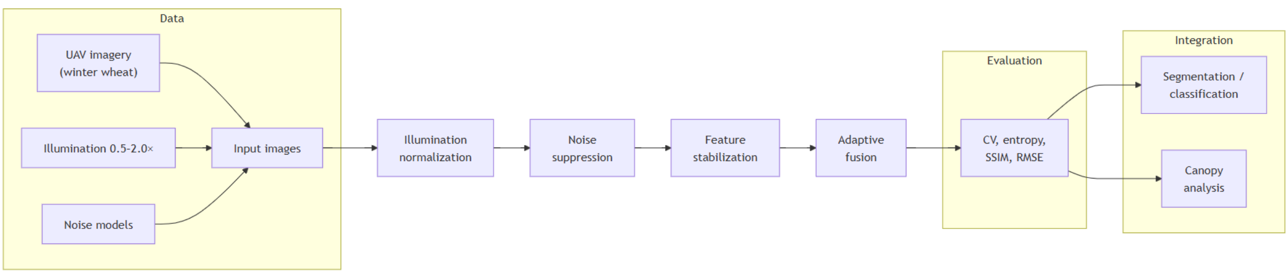

Fig. 1. Architecture of the developed model of preprocessing of multispectral images of winter wheat canopies

The Spectral Feature Stabilization Unit performs normalization and integration of multispectral features while accounting for channel-specific weighting factors derived from a confidence estimation mechanism. In UAV-based imagery of winter wheat canopies, spectral responses vary significantly due to row geometry, leaf orientation dynamics, and local shadowing, which makes channel-wise confidence assessment essential for obtaining stable descriptors. For each pixel, a vector of spectral features is formed:

$$F(x,y)=\frac{I(x,y,\lambda)-\mu_\lambda}{\sigma_\lambda+\varepsilon}, \tag{11}$$

where μ_λ and σ_λ is the mean and standard deviation of intensity in the spectral channel. The final stabilized trait vector is calculated as shown in formula:

$$f_{\text{stable}}=\mathbf{W}f_{\text{raw}}+(1-\mathbf{W})f_{\text{corr}}, \tag{12}$$

where $\mathbf{W}$ is the matrix of weighting coefficients, determined from the condition of minimizing the functionality of instability:

$$J(\mathbf{W})=\sum_{i=1}^{n} f_{\text{raw}}^{(i)}-f_{\text{corr}}^{(i)}\,\|^2+\lambda\,\|\nabla\mathbf{W}\|^2, \tag{13}$$

Such optimization minimizes the influence of local illumination variations on descriptor formation, which is especially critical for the reliable analysis of winter wheat canopies, where row structure and dense foliage produce highly non-uniform reflectance patterns. To evaluate the effectiveness of the proposed model, an experimental setup was created to enable fully automated processing of multispectral image sets of winter wheat under variable lighting and controlled noise conditions. The system included a module for generating illumination variations (simulated cloud cover, solar glare, and partial canopy shading) and noise disturbances with predefined amplitude, which were applied to the input data prior to the preprocessing stage.

The assessment was carried out according to three groups of metrics, applied to multispectral UAV imagery of winter wheat canopies:

1) Trait stability – measured by the coefficient of variation and intersample entropy of normalized descriptors, reflecting the consistency of spectral responses within wheat rows under variable illumination;

2) Structure preservation – evaluated using the SSIM structural similarity index between the original and restored images, ensuring that the geometric characteristics of winter wheat canopies (row alignment, leaf texture, and canopy density) are not degraded during preprocessing;

3) Robustness to noise – quantified through the relative reduction in RMSE for different noise types, which is essential for preserving fine-scale spectral patterns typical of winter wheat fields.

For each experimental series, the model performed batch processing of images in 10 multispectral channels, and intermediate outputs after each processing stage were logged in JSON format for subsequent statistical analysis. Additionally, comparisons were made with baseline normalization methods (Gray World, CLAHE, Homomorphic Filtering), enabling a quantitative assessment of the advantages of the adaptive model in reducing descriptor variability specifically in winter wheat imagery.

The described experimental setup provided a complete automated workflow – from generating illumination and noise variations to computing stability metrics – forming a solid foundation for integrating the model into real-time robotic monitoring systems for winter wheat fields.

The scientific novelty of the proposed approach lies in the integration of entropy-adaptive denoising and instability-driven spectral feature fusion, which together form a unified preprocessing mechanism that has not previously been applied to UAV-based multispectral analysis of winter wheat canopies.

V. RESULTS

The performance of the proposed preprocessing-stabilization framework was evaluated on multispectral UAV imagery of winter wheat canopies using four complementary quantitative metrics: coefficient of variation (CV), entropy (H), structural similarity index (SSIM), and root-mean-square error (RMSE). These metrics collectively characterize the stability, information richness, structural fidelity, and noise robustness of the extracted descriptors under variable field conditions. Figure 2 presents a comparative analysis of the developed method against three widely used baseline approaches – Gray World, CLAHE, and Homomorphic Filtering.

The proposed method demonstrates the lowest CV (0.12), indicating a substantial reduction in spectral variability across canopy regions compared to classical normalization techniques (0.19–0.28). This reduction reflects a higher degree of descriptor stability in heterogeneous lighting environments typical for winter wheat fields. The entropy value increases to 5.9, outperforming all baselines, which suggests that the stabilized descriptors preserve greater spectral information while avoiding oversmoothing. Structural consistency is likewise improved: SSIM reaches 0.923 for the proposed method, compared to 0.78–0.84 for traditional approaches, confirming that the preprocessing pipeline maintains the geometric integrity of the wheat canopy, including its fine-scale textural patterns. RMSE decreases to 0.089, demonstrating improved robustness to synthetic noise representative of varying sensor and acquisition conditions.

Figure 3 further examines the behavior of the method under controlled Gaussian noise. Across all noise levels (σ = 0.01–0.04), the proposed model consistently yields higher SSIM compared to the baseline, with the performance gap widening as noise intensity increases. For example, at σ = 0.03, SSIM decreases to 0.77 for the baseline but remains at 0.88 for the proposed method, indicating that the entropy-adaptive denoising and instability-guided fusion mechanisms effectively preserve structural features even under severe degradation. These results confirm that the hybrid preprocessing chain significantly enhances feature resilience relative to traditional normalization techniques.

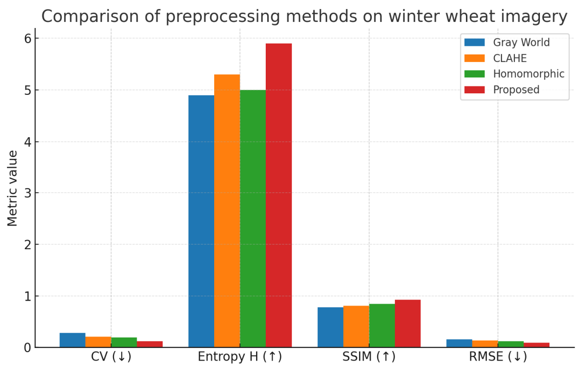

Fig. 2. Comparison of preprocessing methods (Gray World, CLAHE, Homomorphic, Proposed) based on CV, entropy, SSIM, and RMSE metrics for multispectral imagery of winter wheat canopies

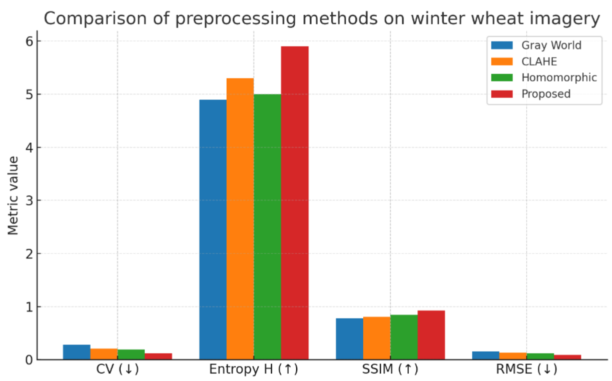

Fig. 3. SSIM performance of the baseline and proposed methods under increasing levels of Gaussian noise (σ = 0.01–0.04) for winter wheat multispectral imagery

Overall, the experimental findings demonstrate that the proposed framework provides stable, structurally consistent, and noise-robust multispectral descriptors for winter wheat canopy analysis. This improvement directly supports downstream computer vision tasks such as segmentation, phenotypic structure estimation, and within-field variability assessment, and enables more reliable integration of UAV-based sensing into real-time precision agriculture workflows.

VI. Conclusions

The conducted research demonstrates that the proposed hybrid preprocessing–feature stabilization framework provides a substantial improvement in the reliability of multispectral UAV-based analysis of winter wheat canopies under real field conditions. By integrating MSRCR-based illumination normalization, entropy-adaptive denoising, and instability-driven spectral fusion into a unified pipeline, the model achieves coordinated gains across all key evaluation metrics. The reduction of the coefficient of variation to 0.12 and RMSE to 0.089, combined with the increase of SSIM to 0.923 and entropy to 5.9, confirms that the method simultaneously enhances descriptor stability, structural fidelity, and information richness. These improvements persist even under escalating noise levels, demonstrating strong resilience to illumination heterogeneity, sensor distortions, and fine-scale canopy texture variations typical of winter wheat fields.

The obtained results validate that preprocessing – not downstream modeling depth – is the decisive factor for reproducible UAV-based crop monitoring, and that early stabilization of multispectral data significantly reduces error propagation into later stages of analysis. Unlike conventional normalization pipelines, the proposed approach maintains geometric and spectral coherence across acquisition dates, noise intensities, and canopy structural conditions, which is crucial for phenotyping, crop status assessment, and within-field variability mapping.

From the standpoint of scientific novelty, the study establishes the first unified preprocessing mechanism that combines entropy-informed spatial-spectral filtering with differentiable instability-minimizing fusion for agricultural UAV imagery. This configuration provides a principled, multi-objective balance between illumination invariance, noise suppression, and preservation of agronomic structures – an aspect not addressed by existing Retinex, LOF, or handcrafted filtering schemes.

The demonstrated efficiency and computational lightness of the model make it suitable for deployment on edge devices integrated into UAVs, autonomous ground robots, and real-time monitoring platforms. Future work should explore coupling the stabilized descriptors with Transformer-based segmentation models, dynamic adaptation of filtering parameters to real environmental telemetry (illumination, humidity, solar angle), and integration with multisensor pipelines (LiDAR, SAR) to increase cross-season generalization. Overall, the proposed method establishes a robust foundational component for next-generation computer-integrated agricultural monitoring systems that require stable, noise-resistant, and phenologically consistent multispectral features.

REFERENCES

[1] IPPC Secretariat. Climate-change impacts on plant pests: a technical resource to support national and regional plant protection organizations. Rome: FAO on behalf of the Secretariat of the International Plant Protection Convention, 2024. 53 p. https://doi.org/10.4060/cd1615en.

[2] C. Zhang, H. Kerner, S. Wang, P. Hao, Z. Li, K. A. Hunt, J. Abernethy, H. Zhao, F. Gao, L. Di, C. Guo, Z. Liu, Z. Yang, R. Mueller, C. Boryan, Q. Chen, P. C. Beeson, H. K. Zhang, and Y. Shen, "Remote sensing for crop mapping: A perspective on current and future crop-specific land cover data products," *Remote Sensing of Environment*, vol. 330, p. 114995, 2025. https://doi.org/10.1016/j.rse.2025.114995

[3] H. O. Velesaca, P. L. Suárez, R. Mira, and A. D. Sappa, "Computer vision based food grain classification: A comprehensive survey," *Computers and Electronics in Agriculture*, vol. 187, p. 106287, 2021. https://doi.org/10.1016/j.compag.2021.106287

[4] K. Halder, A. K. Srivastava, W. Zheng, K. Alsafadi, G. Zhao, M. Maerker, M. Singh, L. Guoging, A. Ghosh, M. Vianna, S. C. Pal, R. Shukla, M. Utthasini, P. Rosso, A. Bhattacharya, U. Chatterjee, D. Bisai, T. Gaiser, D. Behrend, L. Han, and F. Ewert, "A robust and scalable crop mapping framework using advanced machine learning and optical and SAR imageries," *Smart Agricultural Technology*, vol. 12, p. 101354, 2025. https://doi.org/10.1016/j.atech.2025.101354

[5] M. Ashraf, M. Abrar, N. Qadeer, A. A. Alshdadi, T. Sabbah, and M. A. Khan, "A convolutional neural network model for wheat crop disease prediction," *Computers, Materials & Continua*, vol. 75, no. 2, pp. 3867–3882, 2023. https://doi.org/10.32604/cmc.2023.035498

[6] W. Zhang, S. Zhu, D. Han, T. Yang, Y. Jiang, J. Wang, F. Wu, Z. Yao, C. Sun, and T. Liu, "Classification of pre-winter wheat seedling conditions based on UAV images and local optimized features (LOFs)," *Journal of Integrative Agriculture*, 2025. https://doi.org/10.1016/j.jia.2025.07.031

[7] H. Zhou, Q. Li, B. Qin, H. Min, S. Liang, X. Wang, J. Cai, Q. Zhou, M. Huang, D. Jiang, Y. Zhong, and J. Chen, "High-throughput wheat seedling phenotyping via UAV-based semantic segmentation and ground sample distance driven pixel-to-area mapping," *Computers and Electronics in Agriculture*, vol. 238, p. 110819, 2025. https://doi.org/10.1016/j.compag.2025.110819

[8] L. Sandoval-Pillajo, I. García-Santillán, M. Pusdá-Chulde, and A. Giret, "Weed detection based on deep learning from UAV imagery: A review," *Smart Agricultural Technology*, vol. 12, p. 101147, 2025. https://doi.org/10.1016/j.atech.2025.101147

[9] Anderegg J. UAV dataset of nine wheat fields in Switzerland with raw, processed and meta data [Electronic resource] / Jonas Anderegg, Flavian Tschurr // ETH Zurich. – Mode of access: https://doi.org/10.3929/ethz-b-000662770.

Received August 19, 2025

Sineglazov Victor. ORCID 0000-0002-3297-9060. Doctor of Engineering Science. Professor.
Head of the Department Aviation Computer-Integrated Complexes, Faculty of Air Navigation Electronics and Telecommunications, State University "Kyiv Aviation Institute", Kyiv, Ukraine.
Education: Kyiv Polytechnic Institute, Kyiv, Ukraine, (1973).
Research area: Air Navigation, Air Traffic Control, Identification of Complex Systems, Wind/Solar power plant, artificial intelligence.
Publications: more than 800 papers.
E-mail: svm@kai.edu.ua

Koniushenko Roman. Postgraduate Student.
Aviation Computer-Integrated Complexes Department, Faculty of Air Navigation, Electronics and Telecommunications, State University "Kyiv Aviation Institute", Kyiv, Ukraine.
Education: National Aviation University, Kyiv, Ukraine, (2025).
Research interests: artificial neural networks, precision agriculture, programming.

Publications: 1.
E-mail: 4064821@stud.nau.edu.ua

В. М. Синєглазов, Р. С. Конюшенко. Виділення ознак для мультиспектрального аналізу зернових культур із використанням оптимізованих конвеєрів комп'ютерного зору
У статті представлено результати дослідження, спрямованого на підвищення стабільності, відтворюваності та структурної узгодженості процесів комп'ютерного зору під час аналізу мультиспектральних зображень посівів озимої пшениці, отриманих з безпілотних літальних апаратів. Запропоновано нову адаптивну модель попередньої обробки, що поєднує нормалізацію освітленості (модифікований алгоритм Retinex/MSRCR), ентропійно-регульовану просторово-спектральну фільтрацію для придушення шумів та адаптивне спектральне злиття, кероване функціоналом нестабільності, для формування стабільних дескрипторів. Модель сформульована як багатокритеріальна схема попередньої обробки, що одночасно оптимізує інваріантність до освітлення, стійкість до шумів, структурну цілісність та інформаційну насиченість спектральних ознак. Експериментальні дослідження на відкритому наборі даних безпілотних літальних апаратів дев'яти полів озимої пшениці (Швейцарія) показали зменшення коефіцієнта варіації до 0.12 та RMSE до 0.089, а також зростання SSIM до 0.923 і ентропії до 5.9, що суттєво перевищує результати класичних методів нормалізації. Отримані результати підтверджують ефективність розробленого підходу в умовах неоднорідного освітлення та сенсорних спотворень, забезпечуючи стабільне та фенологічно узгоджене вилучення ознак. Запропонована модель може бути інтегрована у комп'ютерно-інтегровані та роботизовані системи точного землеробства для підвищення надійності автоматизованого моніторингу стану посівів озимої пшениці.
Ключові слова: мультиспектральний аналіз; комп'ютерний зір; безпілотний літальний аппарат; точне землеробство; стабілізація ознак.

Синєглазов Віктор Михайлович. ORCID 0000-0002-3297-9060. Доктор технічних наук. Професор.
Завідувач кафедрою авіаційних комп'ютерно-інтегрованих комплексів. Факультет аеронавігації, електроніки і телекомунікацій, Державний університет «Київський авіаційний інститут», Київ, Україна.
Освіта: Київський політехнічний інститут, Київ, Україна, (1973).
Напрям наукової діяльності: аеронавігація, управління повітряним рухом, ідентифікація складних систем, вітроенергетичні установки, штучний інтелект.
Кількість публікацій: більше 800 наукових робіт.
E-mail: svm@kai.edu.ua

Конюшенко Роман Сергійович. Аспірант.
Кафедра авіаційних комп'ютерно-інтегрованих комплексів, Факультет аеронавігації, електроніки та телекомунікацій, Державний університет «Київський авіаційний інститут», Київ, Україна.
Освіта: Національний авіаційний університет, Київ, Україна, (2025).
Напрям наукової діяльності: штучні нейронні мережі, точне землеробство, програмування.
Кількість публікацій: 1.
E-mail: 4064821@stud.nau.edu.ua