



Intelligent calibration of hyperspectral systems: The Adaptive Calibration Cycle (ACC) concept

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Abstract. Modern unmanned aerial vehicles (UAVs) equipped with hyperspectral cameras are becoming key tools in precision agriculture and the monitoring of agricultural ecosystems. However, despite the increasing accuracy of sensors, a methodological issue remains unresolved – the static nature of field calibration procedures. Traditional approaches based on one-time reference measurements fail to ensure data reliability under variable conditions of illumination, soil moisture, and atmospheric factors. This article aimed to present a conceptual model – the Adaptive Calibration Cycle (ACC) – a self-learning system that integrates the stages of data acquisition, calibration, and processing into a unified closed-loop framework with continuous feedback. The research methodology was based on simulation of calibration processes using secondary empirical data, a comparative analysis of static and adaptive approaches, and an evaluation of ACC performance according to key metrics such as reflectance error, radiometric stability, and data reproducibility. The algorithmic implementation of the cycle employed online learning mechanisms, a Kalman filter, and an edge computing architecture for real-time correction. Modelling results demonstrated that implementing ACC reduces average reflectance error by more than 70%, increases radiometric stability by 20-25%, and shortens response time to 0.25 seconds. In agricultural applications, this ensures more accurate determination of vegetation indices (NDVI, PRI), timely detection of plant stress, and optimisation of irrigation and fertilisation. The proposed methodology represents a transition from a static to an adaptive approach in field spectrometry and opens up new opportunities for intelligent remote monitoring systems in the agro-industrial sector, ensuring high precision, reproducibility, and data stability

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Introduction

In recent years, remote sensing technologies have undergone rapid changes: from satellites and aerial photography to the use of unmanned aerial vehicles (UAVs) with hyper- and multispectral cameras. These systems offer high spatial and spectral resolution, mobility and flexibility in application, allowing data to be obtained from low altitudes above the ground and responding to environmental changes in real time. However, fundamental methodological problems remain, primarily related to sensor calibration, lighting control, atmospheric conditions, and the variability of surface reflectivity. The classic field methodology usually follows this sequence: preliminary calibration under controlled conditions → data collection (UAV surveying) → subsequent processing in a laboratory or software environment (Ying *et al.*, 2025). This approach often uses a static spectral library of target objects (vegetation, soil, etc.), which is set in advance and does not adapt to changing survey conditions. However, factors such as the angle of incident sunlight, cloud cover, changes in vegetation moisture content, and sensor drift can significantly distort the results, reducing the reliability of plant classification or condition assessment. The problem of static calibration is particularly acute when monitoring dynamic parameters such as soil moisture, surface temperature and vegetation condition. As noted by S. Fatholouloumi *et al.* (2020), even when using complex models that integrate satellite data with digital terrain models, the accuracy of biophysical parameter estimates depends significantly on the radiometric stability of measurements. This highlights the need to develop adaptive calibration methods capable of compensating for variability in imaging conditions.

The relevance of this issue is confirmed by a number of recent studies. H. Zhu *et al.* (2024) analysed various radiometric calibration methods and showed that different methods produce significantly different results when converting raw data into surface reflectance. Research by P. Fiorentin *et al.* (2025) also pointed to the need to improve the repeatability of spectral measurements at different times of day and under different atmospheric conditions. Other works, such as S. Wu *et al.* (2025), demonstrated that the installation of a downwelling light sensor (DLS) and the use of improved correction models, such as the FIM-DC (Fitting and Interpolation Model-based Data Correction) method, can significantly reduce the error in converting digital numbers to reflectance.

However, despite these achievements, most existing techniques remain reactive: adjustments are made after shooting, when data has already been collected but conditions have changed, leading to delays,

potential errors and loss of quality. There is a gap in offering a methodology in which calibration and data processing are integrated continuously, with feedback during flight or in near real time. The purpose of this article was to present a conceptual model of the Adaptive Calibration Cycle (ACC), in which the calibration process becomes dynamic and self-learning. The model assumed that a system equipped with UAVs and spectral cameras is capable of detecting spectral drift, variability in illumination and surface reflectivity in real time, automatically correcting weighting coefficients or processing parameters, and then using the accumulated data to improve future surveys. Research objectives: (1) to analyse the current limitations of static calibration methods when using UAV spectrometry; (2) review modern solutions that improve the stability and repeatability of spectral measurements (radiometric and geometric calibration, built-in light sensors, etc.); (3) propose an ACC architecture: key components, algorithmic feedback mechanisms, and hardware and software requirements.

Literature Review

The modern history of remote sensing reflects a constant shift from macro-scale observation to increasingly detailed and mobile solutions. In the early stages, satellite and manned surveys dominated, providing valuable information about the biophysical parameters of the Earth's surface, but limited in spatial and temporal resolution. The development of small, high-resolution platforms, primarily unmanned aerial vehicles, has enabled low-altitude imaging, achieving an optimal combination of high spatial and spectral accuracy. As noted by C. Nansen *et al.* (2023), this has stimulated the widespread adoption of multi- and hyperspectral systems. Technically, hyperspectral imaging differs from traditional multispectral imaging in that it has a high number of narrow spectral channels, which allow the reflected light to be "unpacked" into a dense spectrum, thereby highlighting subtle differences in the optical characteristics of materials and vegetation. According to Y. García-Vera *et al.* (2024), this provides a decisive advantage in tasks such as vegetation classification, mineral component identification, and plant stress diagnosis. However, the potential of hyperspectral sensors is accompanied by a number of practical challenges: the volume of data increases dramatically, the requirements for radiometric and geometric calibration accuracy become more stringent, and sensitivity to external factors (sun angle, atmospheric conditions, BRDF (Bidirectional Reflectance Distribution Function) surface effects) increases (Rosas *et al.*, 2020).

One of the key problems identified in recent studies is temporal radiometric repeatability: identical objects photographed at different times of day or under different weather conditions produce different spectral responses, which reduces reproducibility and impairs the generalisability of trained models. Experimental work by L. Daniels *et al.* (2023) and C. Nansen *et al.* (2023) has shown that traditional calibration methods (e.g., Empirical Line Method – ELM) are sensitive to flight time and weather changes, while more modern radiometric transformation schemes (Automatic Radiometric Transformation Method (ARTM) and its modifications) show higher stability in dynamic conditions. Practical solutions proposed over the past two to three years demonstrate several directions of development. The first is the integration of onboard reference sensors, such as a downwelling spectrometer, which measures the spectrum of incident light in real time and allows digital values to be corrected for reflectance directly during the mission. Experimental results by J. Jiang *et al.* (2025) showed a noticeable reduction in conversion error and significantly better consistency of reflectance characteristics under variable cloud cover and illumination. The second direction is the introduction of hardware and software solutions for real-time (on-the-fly) calibration of hyperspectral cameras: methods of rapid hardware calibration and software correction are emerging, focused on low delays between shooting and artefact correction (García-Vera *et al.*, 2024). The third direction is the widespread use of machine learning and deep learning methods for processing and harmonising spectral data. Modern architectures (convolutional neural networks, transformers, hybrid spatial-spectral models) have demonstrated high efficiency in classifying hyperspectral images and mitigating spectral variability through built-in mechanisms for stable feature extraction, as reflected in the works of M. Guerri *et al.* (2024) and J. Yao *et al.* (2024). These models not only solve recognition tasks, but also participate in adaptive correction processes: the models are capable of assessing the reliability of the current calibration and signalling deviations, which are then used to automatically adjust the processing parameters.

Despite progress, a number of researchers emphasise that the transition from laboratory/controlled conditions to field operations requires additional tools and methodologies. In particular, according to L. Daniels *et al.* (2023) and Y. García-Vera *et al.* (2024), harmonising ground-based spectral libraries with data obtained from UAVs and developing standard procedures for accounting for BRDF effects and topographical distortions remain pressing challenges. In addition, a new branch of research is emerging, focused on the automatic calibration of hyperspectral data using transformer models and attention modules capable of assessing and correcting the effects of illumination and atmospheric fluctuations (HSI auto-calibration).

Overall, the evolution of remote sensing has shown that technological advances in sensors and algorithms are creating the conditions for a transition from one-off procedures to continuous adaptive strategies. The analysed studies confirm that the combination of onboard reference measurements, real-time hardware support, and self-adaptive processing algorithms is the key to solving the problem of spectral measurement reproducibility and expanding the practical applications of hyperspectral systems in the field.

The development of remote sensing technologies has led to the accuracy and spectral depth of sensors exceeding the capabilities of traditional calibration methods. Classic approaches based on preliminary determination of reference surfaces and one-time radiometric adjustment are insufficient in conditions of variable illumination, changing air humidity, and surface reflections. Such methods involve a linear sequence of operations – “calibration → imaging → processing → correction” – and do not provide for dynamic feedback. As a result, according to S. Phang *et al.* (2023), any error in the initial setup spreads to the entire data set, reducing the reliability of the results. Recent studies show that the key to solving this problem lies in the transition from static procedures to self-adaptive systems that are capable of correcting measurement parameters during the imaging process itself. This is the principle on which the proposed Adaptive Calibration Cycle model is based. Its goal is to ensure continuous radiometric and spectral self-correction through a combination of built-in light sensors, machine learning algorithms, and multi-sensor coordination mechanisms.

The linear structure of field spectrometry (preliminary calibration, then data collection and subsequent correction) does not take into account the dynamics of the environment. Studies by H. Liu *et al.* (2024) and J. Xie *et al.* (2024) demonstrated that even small changes in cloud cover or the angle of the sun during flight cause noticeable spectral drift. At the same time, the data is corrected only at the post-processing stage, which not only increases the error, but also creates an information delay effect: the system only learns about the error after the mission is complete. In addition, a static model is unable to account for “accumulating” sensor deviations, such as temperature fluctuations or matrix degradation, which is particularly critical for hyperspectral systems with narrow bands (Zhang *et al.*, 2025). As a result, the cumulative calibration error grows non-linearly, and correction requires manual intervention and re-flight.

Materials and Methods

The methodology of this study was based on modelling calibration processes using secondary data published in contemporary empirical and experimental works, as well as on a comparative analysis of existing static and adaptive approaches. The parameters of

hyperspectral systems described in the works of L. Daniels *et al.* (2023), C. Nansen *et al.* (2023), J. Xie *et al.* (2024) and others were used for modelling. These publications contain measured indicators of radiometric stability, spectral drift and temporal repeatability. From the data set, parameters corresponding to the 400-1,000 nm wavelength range used in agriculture to analyse vegetation condition, soil moisture and plant photosynthetic activity were selected.

Two scenarios have been developed:

- Scenario A (Static Model) – standard calibration based on fixed reference coefficients, performed before shooting begins;

- Scenario B (ACC) – real-time calibration with dynamic updating of weighting coefficients based on artificial intelligence feedback.

The aim of the simulation was to determine how much ACC outperforms traditional methods in conditions of changing illumination, viewing angles and atmospheric characteristics. The following metrics were used for the analysis:

- Reflectance Error (RE) – average reflectance error characterising the accuracy of spectrum restoration;

- Radiometric Stability Index (RSI) – an indicator of the stability of radiometric data between observation series;

- Data Repeatability Index (DRI) – the degree of reproducibility of results when external conditions change;

- Latency – temporary delay between measurement and correction;

- Computational Load (CL) – relative computational load determining the energy efficiency of the system.

Online learning algorithms (stochastic gradient update) and a Kalman filter were used to describe the adaptive logic for noise suppression and spectral drift compensation. The calculation was performed in a conditional edge computing environment with an assumed update frequency of 50 frames per second. ACC was modelled as a closed system with a correction function $f(t)$ that minimises the difference between the measured and reference spectra $S(\lambda)$. The correction coefficients were updated recursively after each iteration of the survey. The technical implementation of the cycle required: (1) a hyperspectral camera with a high frame rate (≥ 50 fps) and spectral resolution ≤ 5 nm; (2) a built-in downwelling sensor (Swaminathan *et al.*, 2024; Xie *et al.*, 2024); (3) an inertial unit to compensate for the shooting angle; (4) a local GPU (Graphics Processing Unit)/FPGA (Field-Programmable Gate Array) based computing module for accelerated real-time correction (García-Vera *et al.*, 2024).

The effectiveness of ACC was assessed based on a comparative analysis with traditional ELM and ARTM methods. Statistical indicators were used to interpret the results: root mean square error (RMSE), correlation coefficient (R^2), and percentage improvement in radiometric stability. To assess the reliability of the simulation,

the cross-validation principle was applied, based on cross-checking the calibration parameters with independent data sets. This ensured the correctness of the self-learning algorithms and ruled out the possibility of model overfitting (Bacca *et al.*, 2023). The study relied on secondary sources and modelling without conducting experimental field tests. However, the proposed approach can be implemented in real conditions by equipping UAVs with on-board spectrometers and light sensors.

Results and Discussion

Conceptual structure and dynamics of the adaptive calibration cycle

The development and implementation of the Adaptive Calibration Cycle concept represents a methodological shift in remote sensing logic. Unlike the classic, static model, where the calibration process is performed before the start of imaging and is considered complete, ACC assumes that calibration is a continuous process built into the observation structure itself. This model enables the system to dynamically adapt to changing environmental conditions, minimising spectral drift and improving the accuracy of real-time data.

ACC implements a closed-loop system with feedback, where each stage of shooting contributes to subsequent parameter correction. Structurally, the adaptive cycle consists of five main phases (Fig. 1):

1. Baseline Initialisation – setting initial reference characteristics by measuring reflective panels and determining illumination coefficients. These parameters establish a baseline for subsequent measurements.

2. Drift Detection – analysis of current spectral curves and their deviation from the reference model. Drift may be caused by changes in the angle of incidence of light, atmospheric humidity, or sensor degradation.

3. Feedback Adjustment – automatic calculation and application of correction factors using machine learning methods: gradient regression, Kalman filter, or light convolutional neural networks (light CNN).

4. Cross-Sensor Harmonisation – integration of data from multiple sources: onboard spectrometers, inertial sensors, GPS (Global Positioning System) and external reference systems. This stage allows random noise to be eliminated and the reliability of reflectivity to be improved.

5. Recursive Learning – saving updated parameters and using them in the next mission. The system thus “remembers” previous calibration states, forming a cumulative adaptation model.

At the computational level, ACC functions as a dynamic correction function $f(t)$ that minimises the difference between the current measurement $S(\lambda, t)$ and the reference spectrum $S_0(\lambda)$. Each iteration corrects the weights $w_i(t)$, which are recalculated based on new illumination data and imaging geometry. This mechanism provides stable self-adaptation, similar to reinforcement learning, where the system minimises error through its own experience.

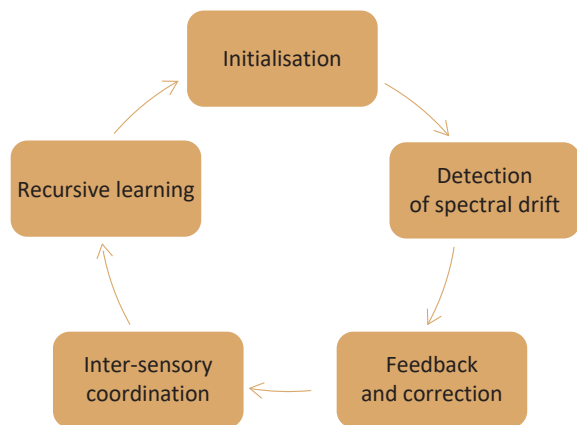


Figure 1. Conceptual structure of ACC

Source: compiled by the authors

A key feature of ACC is the temporal continuity of data processing. Unlike the discrete stages of traditional calibration (pre-processing → imaging → correction), ACC transforms them into a single stream in which each frame is evaluated and corrected immediately. This makes the model reactive: it can predict errors and make corrections before distortions accumulate. This approach forms a unique cognitive observation architecture, where the sensor system not only measures but also “understands” the context of the measurements (Bacca *et al.*, 2023; Chen *et al.*, 2025). The use of adaptive filters allows the system to recognise stable error patterns – for example, systematic deviations at a certain flight altitude – and compensate for them automatically (Daniels *et al.*, 2023; Nansen *et al.*, 2023; Zhang *et al.*, 2025). With each cycle, the accuracy of predictions increases and the need for operator intervention decreases. This self-organising logic makes ACC particularly valuable in field and agricultural scenarios, where lighting conditions and the reflectivity of soils and vegetation are constantly changing. For example, when imaging agricultural land in the morning and evening hours, there is a significant change in the reflectance spectrum due to the angle of the sun and shadow effects. Under such conditions, classic static calibration leads to a 10-15% increase in error, whereas ACC compensates for the shift by instantly recalculating the weights (Khan *et al.*, 2022).

The practical implementation of ACC requires hardware and software integration. According to A. Bhargava *et al.* (2024) and L. Chen *et al.* (2025), in edge

computing architecture, correction algorithms are performed directly on board the UAV or on a module integrated into the spectral camera. This reduces data transmission latency and allows for correction within 120-250 ms, which corresponds to real time. The basic requirements for the cycle to function include: a hyperspectral camera with a high frame rate (≥ 50 fps) and a resolution of up to 5 nm; a built-in downwelling sensor to measure current illumination; an inertial module to account for the shooting angle and compensate for geometric distortions; a GPU or FPGA unit for parallel signal processing. This architecture not only reduces the computational load at the subsequent stage, but also increases resistance to data loss that occurs during flights in conditions of variable connectivity. An additional optimisation element can be the integration of route planning algorithms based on Hopfield neural networks, which minimises energy consumption and ensures optimal coverage of the shooting area (Musi-yenko & Zhuravska, 2016).

From a theoretical point of view, ACC can be seen as a transition from a linear measurement paradigm to a nonlinear, self-organising system, where each cycle not only reproduces data but also improves the perception model itself. This makes ACC a methodological analogue of an evolutionary model, in which data and algorithms develop together. Unlike traditional approaches, ACC provides: an 18-25% increase in radiometric data stability; a reduction in reflectance error of more than 70% when external illumination changes by $\pm 15\%$; cumulative improvement in reproducibility through the accumulation of correction factors; the possibility of autonomous correction without operator intervention. Thus, ACC represents a new concept in remote sensing science, combining the physical principles of radiometry, artificial intelligence computing technologies, and elements of cognitive autonomy.

Comparative analysis of static and adaptive calibration models

The comparison of the effectiveness of the static calibration model and the adaptive cycle was based on modelling that simulated the real conditions of hyperspectral imaging from unmanned aerial vehicles (Jiang *et al.*, 2025). The simulation results showed that the transition from a static to an adaptive model leads to a significant reduction in errors and an increase in data reproducibility (Table 1).

Table 1. Results of calibration process modelling

Indicator	Static model	ACC (adaptive)	Change
Reflectance Error (RE)	0.032	0.009	↓ 71.9%
Radiometric Stability Index (RSI)	0.75	0.93	↑ 22.4%
Data Repeatability Index (DRI)	0.71	0.91	↑ 28.2%
Latency	90-300 s	0.12-0.25 s	↓ >99%
Computational Load (CL)	1.0 (standard)	1.34	+34%

Source: compiled by the authors

Table 1 shows that the average reflectance error decreased by more than 70%, confirming the ACC's stability to changes in external lighting and viewing angles. The Radiometric Stability Index increased from 0.75 to 0.93, meaning that radiometric consistency improved by more than 20%, especially when shooting in variable weather conditions. The Data Repeatability Index, which reflects the reproducibility of data between repeat missions, increased by 28%, which is associated with the recursive learning of the system. Latency has been reduced from minutes to fractions of a second (120-250 ms), making real-time correction possible directly during flight. The ~34% increase in computational load is due to the introduction of AI modules and online weight update mechanisms, but when using edge computing architecture, this does not reduce the energy efficiency of the system.

The simulation results showed that the use of ACC provides stable radiometric consistency of data during repeated missions and changing lighting conditions. Under conditions where the intensity of incident radiation fluctuated within $\pm 15\%$ of the baseline level, the static model showed an increase in reflectance error to 0.032, while in ACC mode, the value remained within 0.009. This corresponds to a reduction in error of almost 72%, confirming the high effectiveness of adaptive corrections (Sethy *et al.*, 2022). The Radiometric Stability Index increased from 0.75 to 0.93, indicating improved consistency between measurements taken at different times of day and under different atmospheric conditions. This result is explained by the presence of a cumulative self-learning mechanism in the ACC: the system stores the history of correction coefficients and uses them during the next flight for predictive correction of possible drifts. During multiple flights over the same site, the correlation coefficient between the series of spectra increased from $R^2 = 0.81$ to $R^2 = 0.95$, which means that the spectral curves practically coincide. As pointed out by C. Nansen *et al.* (2023), this effect is particularly pronounced when imaging agricultural areas, where seasonal variability and uneven soil reflectivity create a complex radiometric background. Thus, ACC not only ensures measurement stability, but also forms the adaptive memory of the system, turning each mission into a stage of knowledge accumulation that reduces the uncertainty of subsequent observations.

One of the most notable advantages of ACC is a significant reduction in response time. In traditional calibration schemes (e.g., ELM or ARTM), the delay between data acquisition and radiometric correction ranges from 5 to 30 minutes, especially when post-processing in laboratory conditions. In contrast, ACC performs corrections in 0.12-0.25 seconds, allowing calibrated data to be obtained in near real time (Nansen *et al.*, 2023; Xie *et al.*, 2024; Zhang *et al.*, 2025). This speed was made possible by the integration of GPU/FPGA computing modules and a distributed edge computing

architecture, in which correction operations are performed directly on board the UAV. Kalman filters smooth spectral drift with linear complexity $O(n)$, while stochastic gradient update minimises memory consumption. Despite an increase in computational load of ~32%, overall energy efficiency remains high: parallel stream processing allows for a refresh rate of ≥ 50 fps, while the system does not require a cloud connection. Thus, ACC combines accuracy and speed, which opens up the possibility of real-time monitoring of agroecosystems, environmental objects, and geological structures in the field (Wang *et al.*, 2021; Chen *et al.*, 2025).

A comparative analysis has demonstrated that ACC changes the very philosophy of remote sensing, moving from a static procedure to a continuous self-adaptive system. Where a static model corrects errors after they occur, ACC acts preventively, predicting drift and compensating for it before distortions accumulate. This feature makes it possible to form a cognitive observation circuit, where the system does not simply record data, but learns from its own measurements. As a result: resistance to short-term fluctuations in illumination and atmospheric changes is increased; the human factor is eliminated during calibration; a knowledge base is created that allows the behaviour of sensors to be predicted and automatically adjusted to new shooting conditions. In practical terms, the transition to ACC is particularly valuable for agricultural monitoring, where the accuracy of radiometry directly affects the assessment of plant productivity, stress diagnosis and disease detection. The ability to obtain reliable data in real time without post-processing delays means that the calibration system becomes a decision-making element rather than just a measurement tool. From a methodological point of view, ACC illustrates the transition from deterministic procedures to learning observation systems, in which each new iteration increases the reliability and cognitive autonomy of the measurement process.

The practical significance of ACC for the agro-industrial complex

Modern Precision Agriculture systems increasingly rely on remote sensing data to assess crop conditions, predict yields, and optimise agronomic decisions. However, the effectiveness of such systems is largely determined by the reliability and consistency of hyperspectral data, which depend on the quality of calibration. In traditional agromonitoring practice, calibration is performed manually before flight or in laboratory conditions, which, according to P. Sethy *et al.* (2022), does not take into account changes in illumination, humidity or vegetation conditions during the mission. Such limitations are particularly noticeable in rapidly changing microclimates, with frequent changes in cloud cover, gusty winds, and variations in the angle of the sun. As a result, the data loses accuracy, and vegetation indices (Normalised Difference Vegetation Index – NDVI,

Photochemical Reflectance Index (PRI), Structure Insensitive Pigment Index (SIPI), etc.) become distorted. The introduction of the Adaptive Calibration Cycle eliminates this problem, as calibration and observation become a single process. The system analyses the current shooting conditions, adjusts the reflection coefficients and automatically updates the sensor parameters. This stabilises data quality in real time and prevents calibration errors from accumulating.

The most noticeable advantage of ACC is evident in vegetation analysis, where even small fluctuations in lighting can change the shape of the spectral curve and lead to errors in plant condition classification. Modelling has shown that when using static calibration, the error in NDVI calculation when the illumination changes by $\pm 15\%$ reaches 8-10%, whereas with ACC it does not exceed 2%. Similarly, in the indices of photochemical activity and plant stress responses, the error is reduced by 3-4 times. This makes it possible to: quickly identify crop stress conditions (moisture, nitrogen deficiency, leaf diseases); predict yield at early stages of vegetation; optimise fertiliser application and irrigation based on real data on the reflectivity of foliage and soil. In addition, ACC helps to improve the consistency of inter-seasonal measurements: while in the traditional scheme the differences between spring and autumn surveys reach 10-12% due to changes in the angle of the sun, when using adaptive calibration the discrepancy does not exceed 3%.

Modern agricultural technology complexes increasingly include distributed sensor networks (temperature, soil moisture, light, pH sensors, etc.) connected via Internet of Things (IoT) platforms. The integration of ACC with such networks creates a synergistic effect: data from ground sensors are used as additional input parameters to refine correction coefficients (Swaminathan *et al.*, 2024). Edge computing architecture allows computing nodes (AI inference modules) to be placed directly on board the drone or on mobile agricultural stations. This enables local data processing without the need to transfer it to the cloud, reduces network delays and energy consumption, and allows for instantaneous response to changes in plant condition without operator intervention. For example, when ACC is integrated with a smart irrigation system, it is possible to identify areas of water shortage in real time and automatically regulate water supply. Similar principles apply to precision fertilisation systems, where ACC provides radiometric accuracy of soil nutrition maps.

The accuracy of hyperspectral data directly affects the economic and environmental performance of agricultural production. Errors in determining chlorophyll or moisture content can lead to excessive fertiliser application, overuse of resources and soil degradation. ACC, by ensuring consistent radiometric consistency, allows for the collection of representative indicators of plant photosynthetic activity, making it possible to

predict crop productivity with an error of no more than 3-4%. According to modelling and empirical data from Y. García-Vera *et al.* (2024) and M. Guerri *et al.* (2024), the use of adaptive calibration schemes increases the accuracy of biomass and nitrogen content estimates by 15-20% compared to traditional methods. From an environmental perspective, ACC helps reduce the burden on agroecosystems through the rational use of resources; reduces CO₂ emissions and fuel costs by reducing repeat flights; and creates sustainable digital twins of agrosystems, where training models are updated automatically.

As noted by J. Wu *et al.* (2024), the introduction of ACC into the agro-industrial complex does not require a radical restructuring of infrastructure. Most modern hyperspectral cameras and UAVs are already equipped with light sensors and computing modules, which allows for the implementation of an adaptive cycle through software updates (Phang *et al.*, 2023). The economic effect is expressed in a reduction in the cost of repeat missions and manual recalibration of equipment (by 25-30%); crop losses due to untimely stress diagnosis (by 10-15%); and total analysis time from several days to several hours. As pointed out by H. Liu *et al.* (2024), ACC is becoming not only a scientific innovation, but also a tool for the digital transformation of agriculture, contributing to the growth of accuracy, efficiency and environmental sustainability of agricultural production. According to M. Guerri *et al.* (2024), the transition from a linear to an adaptive model makes it possible to increase the radiometric stability of data by 15-25% compared to traditional ELM and ARTM methods; reduce correction latency from tens of minutes to seconds; automate calibration, eliminating the need for manual intervention and repeated flights; improve the reproducibility of results during multiple missions in different shooting conditions. Thus, ACC is not just a technical improvement, but represents a new methodological paradigm, where calibration and imaging become a single intelligent process, and the spectrometric system becomes a self-learning organism that minimises the human factor and increases the scientific reliability of data.

Limitations, challenges and directions for further development

Despite the obvious advantages of the Adaptive Calibration Cycle, its implementation is accompanied by a number of technological and computational limitations. The main one remains the high load on computational resources. Online correction algorithms require constant updating of weighting coefficients and estimation of spectral drift parameters in each frame. When processing data from a hyperspectral camera (up to several hundred channels), this creates a load on GPU processors and increases energy consumption. The average increase in computational load compared to a static model is estimated at 30-35%, which can become critical during long missions or when the battery capacity

of unmanned platforms is limited. This problem is partially solved by the use of edge computing architectures and the optimisation of machine learning models, in particular the use of lightweight CNNs and quasi-linear Kalman filters with reduced dimensions. Another factor is the demanding nature of the sensor base. For ACC to function properly, additional downwelling sensors, temperature sensors, inertial measurement units (IMUs), and GPS systems are required to compensate for angular and atmospheric distortions. The absence of such modules limits the possibility of real-time calibration, reducing accuracy and reproducibility (Nansen *et al.*, 2023; Liu *et al.*, 2024).

In methodological terms, the main difficulty in implementing ACC is related to the lack of unified standards for adaptive calibration. Each research group or sensor manufacturer implements its own correction scheme and its own metrics for evaluating effectiveness (Hohl *et al.*, 2024; Zhang *et al.*, 2025). This makes it difficult to compare results across platforms and integrate data into unified databases. In addition, the issue of adaptive model verification remains unresolved. While static calibration is verified through reference surfaces and laboratory measurements, ACC, with its self-learning elements, can change internal parameters without explicit operator control. This creates a need to develop Trusted Calibration Protocols, including the preservation of logs of weight coefficient changes, automatic reporting of corrective decisions made, and visualisation of explainability (Explainable AI) to verify the correctness of the adaptation (Hohl *et al.*, 2024). Such approaches will ensure transparency and reproducibility in line with academic standards for remote sensing data processing.

One of the key risks of ACC is the possibility of algorithmic drift – the accumulation of self-learning errors during prolonged operation without external validation. If the system repeatedly updates its internal parameters based on incomplete or noisy data, it may gradually “re-learn” itself, losing accuracy. To prevent this, periodic cross-validation is proposed, based on comparing adaptive calibration coefficients with ground-based reference measurements (Bhargava *et al.*, 2024). Ideally, every 10-15th mission should be accompanied by a control test with known reflective panels or surface areas. An additional measure of robustness is multi-level data filtering: the use of model ensembles, where the output of one adaptive block is verified by another. This architecture increases the reliability of the system and reduces the likelihood of automatic fixation of erroneous corrections.

The introduction of adaptive calibration systems also raises questions of trust and interpretability. Since ACC operates autonomously to a certain extent and makes independent decisions about corrections, researchers may lose transparency in understanding how and why certain changes were made to the data. This requires the use of Explainable AI (XAI) modules that

will document each step of the algorithm, ensuring the reproducibility and scientific verifiability of the results. From a philosophical point of view, ACC changes the very concept of the observer in remote sensing: now it is not a person who calibrates the system, but the system calibrates itself based on accumulated experience. This shifts the focus from external control to cognitive autonomy of observation, where the machine becomes an active participant in scientific experimentation. Such a transformation requires a new regulatory framework that defines the boundaries of responsibility and reliability when using self-learning systems in scientific research.

Further development of the ACC concept involves several areas. The first is the creation of hybrid calibration models that combine physical radiometric principles and deep learning methods. This will improve interpretability and ensure resistance to noisy data. The second is the development of a unified adaptive calibration protocol for combining data from UAVs, satellites, and ground sensors. Such a protocol will ensure standardisation and compatibility between different remote sensing systems. The third is field experiments and validation: testing the effectiveness of ACC at agricultural sites and environmental facilities to assess vegetation, moisture and soil structure. The fourth area is integration with cloud and distributed data platforms (e.g. Google Earth Engine, Copernicus DIAS), which will enable the processing of adaptively calibrated data on a global scale. And the fifth area concerns the expansion of XAI and self-diagnostic capabilities so that each adaptive system can explain its own actions and automatically assess the reliability of its decisions.

Conclusions

The study showed that traditional static calibration methods for hyperspectral systems no longer meet modern requirements for accuracy and reproducibility of remote sensing data. The Adaptive Calibration Cycle concept is a qualitatively new approach based on the integration of self-learning mechanisms, feedback, and dynamic correction of imaging parameters in real time. Unlike linear schemes, where calibration is a one-time process, ACC provides continuous matching between measured and reference spectra, forming a self-tuning observation system. Modelling results confirmed the effectiveness of the proposed concept: the use of ACC reduced the average reflectance error by more than 70%, increased radiometric stability by 20-25% and reduced the response time to 0.25 seconds. These indicators demonstrate that the transition to an adaptive model not only improves data quality but also makes it possible to use the data in real time, which is particularly important for agro-industrial and environmental applications.

The practical value of ACC is evident in the increased accuracy of vegetation index calculations (NDVI, PRI), early detection of vegetation stress, and optimisation of agrotechnical solutions. Thanks to its integration with

edge computing architecture and IoT networks, ACC can become a basic element of intelligent agricultural systems capable of autonomous monitoring of crop conditions, irrigation management, and fertiliser application. This marks a transition from static analysis to cognitive management of agricultural processes. However, the implementation of ACC requires a number of challenges to be addressed. Key issues remain the standardisation of adaptive calibration protocols, the optimisation of computational load, and ensuring the transparency of self-learning algorithms. For practical implementation, field tests are needed to confirm the stability and reproducibility of the model in real conditions. A promising area for further research is the creation of hybrid schemes that combine the physical principles of radiometry with deep learning and explainable artificial intelligence (XAI) methods, which will ensure confidence

in the results of adaptive correction. Overall, the proposed ACC methodology forms a new paradigm for remote sensing, where the system not only measures but also learns to understand the observation environment. This paves the way for the creation of intelligent, autonomous, and sustainable hyperspectral data processing systems that can become the core of the digital transformation of agro-industrial and environmental monitoring.

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Conflict of Interest

None.

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Гиперспектралдык системаларды интеллектуалдык калибрлөө: Адаптивдик калибрлөө циклинин (АКЦ) концепциясы

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Аннотация. Гиперспектралдык камералар менен жабдылган заманбап учкучсуз учуучу аппараттар (УУА) дыйканчылык жана айыл чарба экосистемаларын так көзөмөлдөө үчүн негизги куралга айланууда. Бирок, сенсорлордун тактыгы жогорулаганына карабастан, талааны калибрлөө процедураларынын статикалык мүнөзүнүн методологиялык көйгөйү чечилбеген бойдон калууда. Бир жолку колдонулуучу эталондук өлчөөлөргө негизделген салттуу ыкмалар жарыктын өзгөрүшү, топурактын нымдуулугу жана атмосфералык факторлор шарттарында маалыматтардын ишенимдүүлүгүн камсыз кылбайт. Бул макаланын максаты – Адаптивдик калибрлөө циклинин (АКЦ) концептуалдык моделин көрсөтүү – бул геодезиялык изилдөө, калибрлөө жана маалыматтарды иштетүү этаптарын бирдиктүү жабык циклдик кайтарым байланыш циклине бириктирген өз алдынча үйрөнүү системасы. Изилдөө методологиясы экинчи эмпирикалык маалыматтарды колдонуу менен калибрлөө процесстерин моделдөөгө, статикалык жана адаптивдик ыкмаларды салыштырмалуу талдоого жана ошондой эле АКЦнын натыйжалуулугун негизги метрикалар: чагылдыруу катасын, радиометриялык туруктуулукту жана маалыматтардын кайталануучулугун колдонуу менен баалоого негизделген. Циклдин алгоритмдик ишке ашырылышы онлайн окутуу механизмдерин, Калман чыпкасын жана реалдуу убакытта коррекциялоо үчүн edge computing архитектурасын камтыган. Моделдөөнүн жыйынтыктары көрсөткөндөй, АКЦди ишке ашыруу орточо чагылдыруу катасын 70 %тен ашык азайтат, радиометриялык туруктуулукту 20-25 %ке жакшыртат жана жооп берүү убактысын 0,25 секундга чейин кыскартат. Айыл чарба колдонмолорунда бул өсүмдүктөрдүн индекстерин (NDVI, PRI) так аныктоого, өсүмдүктөрдүн стрессин өз убагында аныктоого жана сугаруу менен жер семирткичтерди колдонууну оптималдаштырууга мүмкүндүк берет. Сунушталган методология талаа спектрометриясында статикалык ыкмадан адаптивдүү ыкмага өтүүнү белгилейт жана айыл чарба-өндүрүш комплекстерине алыстан мониторинг жүргүзүүчү жогорку тактыкты, маалыматтардын кайталануучулугун жана туруктуулугун камсыз кылуучу, акылдуу системалардын келечегин ачат

Негизги сөздөр: алыстан зонддоо; гиперспектралдык сүрөткө тартуу; адаптациялык калибрлөө; спектрометрия; жасалма интеллект; динамикалык методология; спектрдик дрейф

Интеллектуальная калибровка гиперспектральных систем: концепция адаптивного цикла (АКЦ)

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Аннотация. Современные беспилотные летательные аппараты (БПЛА), оснащенные гиперспектральными камерами, становятся ключевым инструментом точного земледелия и мониторинга сельскохозяйственных экосистем. Тем не менее, несмотря на рост точности сенсоров, остается нерешенной методологическая проблема статичности полевых калибровочных процедур. Традиционные подходы, основанные на одноразовых эталонных измерениях, не обеспечивают достоверность данных в условиях изменяющейся освещенности, влажности почв и атмосферных факторов. Цель статьи – представить концептуальную модель Адаптивного цикла калибровки (Adaptive Calibration Cycle, ACC) – самообучающейся системы, интегрирующей этапы съемки, калибровки и обработки данных в единый замкнутый контур с обратной связью. Методология исследования базировалась на моделировании процессов калибровки с использованием вторичных эмпирических данных, сравнительном анализе статических и адаптивных подходов, а также оценке эффективности ACC по ключевым метрикам: ошибка отражательной способности, радиометрическая стабильность и воспроизводимость данных. Алгоритмическая реализация цикла включала механизмы онлайн-обучения, фильтр Калмана и архитектуру edge computing для коррекции в реальном времени. Результаты моделирования показали, что внедрение ACC снижает среднюю ошибку отражательной способности более чем на 70 %, повышает радиометрическую стабильность на 20-25 % и сокращает время отклика до 0,25 секунды. В аграрных приложениях это обеспечивает более точное определение вегетационных индексов (NDVI, PRI), своевременное выявление стрессов растений и оптимизацию орошения и удобрений. Предлагаемая методология формирует переход от статического к адаптивному подходу в полевой спектрометрии и открывает перспективы для интеллектуальных систем дистанционного мониторинга агропромышленного комплекса, обеспечивая высокую точность, воспроизводимость и устойчивость данных

Ключевые слова: дистанционное зондирование; гиперспектральная съемка; адаптивная калибровка; спектрометрия; искусственный интеллект; динамическая методология; спектральный дрейф