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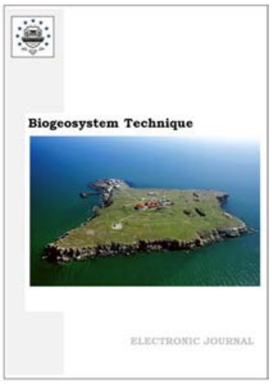

Invasive Plant Monitoring in Hard-To-Reach Areas Using Swarms of Agricultural Drones

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Abstract

The article is devoted to the issues of organization of monitoring and control of invasive plants growing in hard-to-reach places using a swarm of drones and a drone port. Sosnovsky's hogweed has spread widely in Russia and is actively seizing new areas, creating infestation steps that are difficult to control using traditional methods. Monitoring and elimination of such foci by traditional manual methods is time-consuming, ineffective and unsafe.

A new technology that provides rapid monitoring of large areas and targeted chemical intervention only where necessary, reducing the risk of damage from invasions and the use of pesticides, is a technology based on the use of a drone swarm in conjunction with a drone port. It allows you to quickly explore large areas and get detailed images of growing vegetation from different angles. The resulting images can be recognized by means of artificial intelligence, analyzing the density of growth of invasive plants and their proximity to other crops.

The data collected by agrodrones can be conditionally divided into digital and graphical. When receiving digital data from a swarm of drones, the information on the drone port is cleaned of noise and checked for consistency to ensure the reliability of the data, which improves the efficiency of system maintenance. For graphic data, first of all, color correction is used, restoring color details and increasing clarity, while restoring the natural image distorted at the time of digitization and subsequent processing.

The key issue is the merging of the data collected by the agrodron swarm. Different specimens of agrodrons can receive different parameters and different images of the same habitat of invasive

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plants, and these data need to be linked to each other, eliminating contradictions. After building a consistent model of the area, the growing plants are recognized using artificial intelligence.

The described technology allows automated analysis of the vegetation condition and provides conclusions and recommendations based on artificial intelligence.

Keywords: invasive plants, swarm of agricultural drones, data cleaning, data fusion.

1. Problem Statement of Monitoring

Weed infestation presents a pressing issue in agriculture, significantly reducing crop yields and, in certain cases, posing serious threats to ecosystems, agricultural productivity, and human health. In Russia, the spread of Heracleum sosnowskyi (Sosnowsky's hogweed) is particularly acute. This plant forms dense thickets up to 3 meters tall and secretes a toxic sap that causes severe phytophotodermatitis in humans. Ambrosia artemisiifolia (common ragweed) has become widespread in southern regions, triggering potent allergic reactions – its pollen being a notorious allergen – and diminishing field productivity (Müllerová, 2024) Solidago canadensis (Canada goldenrod) and related species aggressively displace native flora, establishing monocultures that degrade pollinator habitats and disrupt ecosystem services These and other invasive weeds continuously colonize new territories, creating invasion foci that are difficult to control using conventional methods.

Traditional manual approaches to monitoring and eradicating such infestations are labor-intensive, time-consuming, inefficient, and potentially hazardous. For example, ground-based surveys of hogweed-infested areas are impeded by the risk of chemical burns while locating ragweed across expansive fields demands substantial human resources. Moreover, blanket pesticide application over entire fields results in excessive chemical loading on the environment. Thus, novel technologies are required that enable rapid, large-scale monitoring and facilitate precise, localized interventions only where necessary – thereby mitigating ecological damage and minimizing chemical usage.

The advancement of unmanned aerial vehicles (UAVs), or agricultural drones, offers transformative potential in addressing this challenge. UAVs allow rapid coverage of extensive areas and provide high-resolution visual data through aerial imagery (Figure 1). They enable timely and comprehensive field inspections, facilitate the identification of weed clusters, reduce inspection time, and permit detailed, multi-angle examination of detected infestations (Monteiro, Santos, 2022). Artificial intelligence (AI) algorithms can then be applied to classify plant species visible in the captured images (Dutech, Scherrer, 2013).

Although the deployment of agricultural UAVs remains somewhat limited in Russia at present, the topic of agro-drones remains highly relevant – not only domestically but globally. Increasingly, "smart" technological solutions are emerging that reduce operational costs and optimize agro-industrial complex (AIC) workflows. Drones play a pivotal role in the digital transformation of the AIC. Consequently, UAV developers continue to introduce increasingly sophisticated and multifunctional models tailored to diverse agricultural tasks.

Fig. 1. Application of agricultural drones in farming

Of particular interest is the use of drone swarms – coordinated groups of UAVs operating in conjunction with a central droneport. While a single drone is constrained by flight range and endurance, a swarm can efficiently cover large areas and complete missions far more effectively. Cooperative control necessitates robust inter-drone communication and avoidance of task duplication. Modern algorithms enable real-time data exchange and collaborative coverage path planning, wherein each UAV autonomously computes its flight trajectory while accounting for the plans of others. Distributed coordination and information sharing maximize area coverage while minimizing energy consumption. A key challenge lies in the preliminary processing and cleaning of acquired data, as well as its fusion across multiple UAVs and the resolution of inconsistencies between overlapping observations.

2. Hardware Configuration for Monitoring

To perform monitoring tasks effectively, a drone must be equipped with the following instrumentation:

1. A high-resolution camera for capturing detailed imagery;
2. An ultrasonic sensor for obstacle detection and collision avoidance;
3. A Bluetooth module for short-range data transmission;
4. A GPS receiver for geotagging the location of each data capture;
5. An accelerometer for maintaining horizontal stabilization and minimizing deviations;
6. A barometric sensor (barometer) for altitude hold;
7. An autopilot system for autonomous waypoint navigation and return-to-home functionality.

The drone must incorporate obstacle-avoidance sensors capable of triggering evasive maneuvers upon detecting obstructions. Its internal control system should enable autonomous flight along pre-defined routes even in the event of communication loss with the ground control station.

The drone must be outfitted with a high-resolution camera, as it is required to approach a designated field segment, descend to a low altitude, and capture multiple high-quality images. Upon mission completion, the collected data must be transmitted to the droneport, where specialized software leveraging AI algorithms performs subsequent analysis and interpretation.

3. Data Cleaning

Data acquired by agricultural drones can be broadly categorized into two types: digital (numerical sensor readings) and graphical (imagery).

All transmitted and received signals inherently contain noise – defined as any undesirable signal component superimposed on the ideal signal. In digital wireless communication systems, the ideal signal resembles a trapezoidal pulse, which becomes distorted in the presence of noise (Figure 2; Li, 2009).

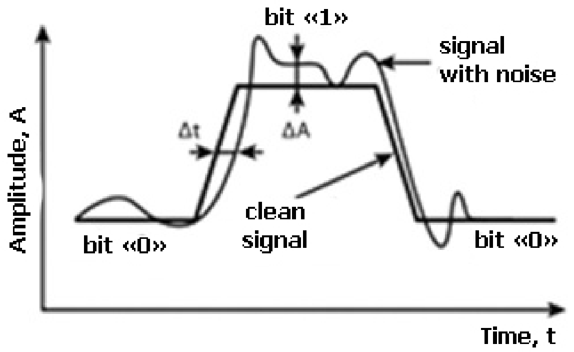

Fig. 2. Ideal vs. real signal waveforms

Deviations from the ideal can be observed in both time (temporal jitter) and amplitude (amplitude noise). In radio-frequency systems, signal amplitude corresponds to power; thus, amplitude deviation (dA) represents amplitude noise, while temporal deviation (dt) constitutes jitter.

Jitter-unwanted timing instability – manifests as fluctuations in the temporal positioning of signal transitions relative to their nominal values. It arises from synchronization instability and channel path variations. Jitter comprises two components: a purely random (stochastic) component and a quasi-deterministic, typically low-frequency component known as wander (Smagin, 2012).

The effects of jitter and amplitude noise on system performance are asymmetric. Amplitude noise acts as a continuous function, exerting a persistent influence on system characteristics. In contrast, jitter affects the system only during signal edge transitions.

Signal integrity is generally defined as any deviation from the ideal signal waveform. Thus, it encompasses both amplitude noise and jitter. However, certain integrity issues – such as undershoot, overshoot, and signal ringing – cannot be fully characterized solely by jitter and noise metrics (Figure 3).

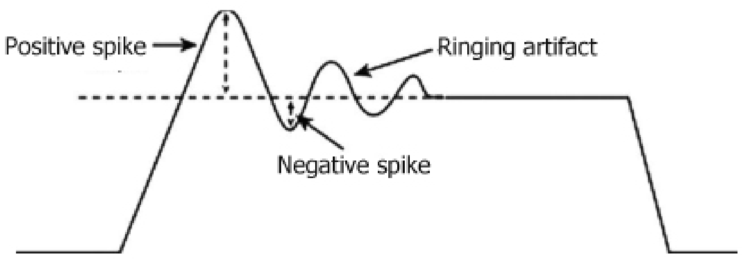

Fig. 3. Characteristics of signal integrity

The combined impact of jitter and amplitude noise is best evaluated from the perspective of the receiver in a communication system. The receiver samples the incoming pulse at time t using a voltage threshold v (Figure 4). In the ideal case, sampling occurs at the center of the input pulse. If the rising and falling edge times satisfy t_f < t_s and the signal voltage V₁ > v_s, the system correctly registers a logical “1” (Figure 4a).

In the presence of jitter and noise, signal edges shift along the time axis and voltage levels fluctuate along the amplitude axis. This may violate the conditions for correct bit detection, leading to bit errors (e.g., a logical “1” misinterpreted as “0”). Three failure modes may occur during “1” detection:

1. The rising edge crosses the threshold after the sampling instant (t_f > t_s);

2. The falling edge crosses before the sampling instant (t_f < t_s);

3. The signal voltage falls below the threshold (V₁ < v_s).

For logical “0” detection (Figure 4b), correct sampling requires t_r < t_s < t_f and V₀ < v_s. Violations mirror those for “1,” except that V₀ > v_s leads to error.

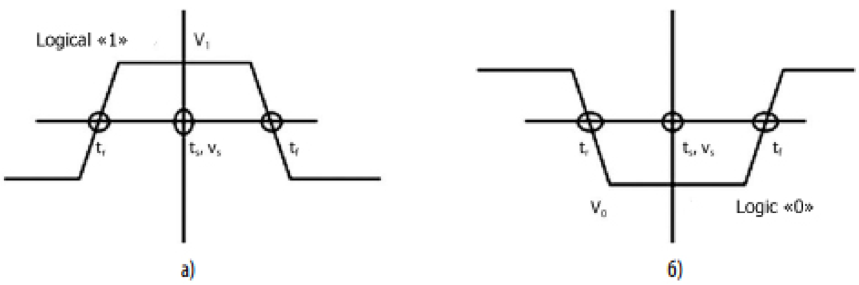

Fig. 4. Receiver-based sampling of input data

Given that digital systems transmit numerous bits over time, overall performance is commonly quantified by the Bit Error Rate (BER) – the ratio of erroneous bits (N_{err}) to total transmitted bits (N_{tot}). BER serves as a fundamental quality metric for communication systems. At multi-gigabit-per-second data rates, standards such as Fibre Channel, Gigabit Ethernet, SONET, and PCI Express typically require BER ≤ 10^{−12}, meaning no more than one error per trillion bits. Higher BER degrades network efficiency and increases system latency. BER depends on data rate, jitter, and noise, and – being statistical – is often analyzed using Poisson statistics.

Jitter and noise originate from numerous physical and systemic sources, broadly classified as intrinsic and extrinsic. Intrinsic sources stem from the stochastic behavior of electrons and holes in semiconductor devices and represent fundamental physical limits that cannot be fully eliminated – though they may be minimized. Extrinsic sources arise from system design and configuration and are thus potentially correctable.

Intrinsic noise primarily results from thermal and shot noise in electronic and optoelectronic components, setting baseline constraints on system dynamic range. Noise is typically quantified in terms of voltage, current, or power – collectively referred to as “amplitude.” When amplitude noise $\Delta A(t)$ is superimposed on a base signal $A_0(t)$, the corresponding timing jitter can be approximated via linear small-signal perturbation theory:

$$
\Delta t \approx \frac{\Delta A(t)}{dA_0/dt}
$$

where dA_0/dt is the signal slew rate (Figure 5). Thus, for a given amplitude noise level, timing jitter decreases as the signal edge steepness increases – highlighting the benefit of minimizing rise/fall times to reduce jitter.

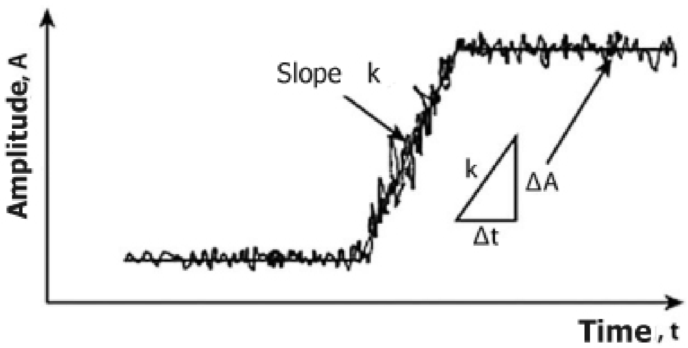

Fig. 5. Conversion of amplitude noise into timing jitter according to linear perturbation theory

Extrinsic noise and jitter arise from system-level imperfections and are amenable to mitigation. Common types include periodic modulation (phase, amplitude, or frequency), duty cycle distortion, inter-symbol interference, crosstalk, electromagnetic interference (EMI), and reflections due to impedance mismatches.

Digitally acquired sensor data undergoes preliminary filtering on board the drone or at the droneport processor to prevent heavily corrupted data from entering the operational database. Cleaned data is then accumulated in real time within a centralized data repository.

Effective noise filtering enhances measurement accuracy (Baklanov, 1998) and sensor reliability. Two primary noise types must be addressed: (1) stationary (additive white Gaussian noise) with relatively stable amplitude, and (2) impulsive noise caused by external disturbances.

For stationary noise, the moving average filter is well-suited: it maintains a buffer of recent measurements and shifts the observation window forward with each new sample. Although this method involves floating-point calculations that slightly slow processing, the overhead remains negligible compared to data transmission latency (FourWeekMBA, 2025).

Impulsive noise within individual measurements is best mitigated using a median filter (Smagin, 2012). Empirical studies show that combining median filtering with moving average yields robust results.

Of special interest is the filtering of the quasi-deterministic jitter component, which primarily reflects hardware-specific characteristics. To isolate this component, we propose the “Caterpillar” method – also known as Singular Spectrum Analysis (SSA). A key advantage of SSA is that it requires no prior model of the jitter process. SSA decomposes a time series into interpretable components (trend, periodicities, noise) by embedding the series into a trajectory matrix, performing singular value decomposition (SVD), and reconstructing selected components. This approach outperforms conventional time-series methods in separating structured signal features from noise.

Following onboard preprocessing, cleaned data is transmitted via communication channels to the central droneport computer for advanced analysis.

Graphical data – i.e., aerial imagery – also requires cleaning. This includes correcting or removing corrupted information such as duplicates, missing values, incorrect formats, and outliers.

Color correction is an essential step in digital image processing. Manual white balance settings on cameras often introduce uncontrolled color inaccuracies. Although modern image editors provide powerful correction tools, manual intervention is impractical in high-throughput workflows. Fortunately, automated color correction solutions exist.

Image quality enhancement focuses on restoring natural color fidelity and improving sharpness – reversing distortions introduced during capture or digitization. Advanced algorithms automatically identify regions requiring adjustment (e.g., color balance, brightness, contrast) and apply localized corrections. These systems also address common artifacts such as moiré patterns and color casts.

Sophisticated color grading leverages blending algorithms and lookup tables (LUTs) to not only restore faded colors but also modify the original color palette as needed.

Professional tools such as iCorrect EditLab – a plugin for Adobe Photoshop and other leading graphic editors – offer fully automated color correction (SmartAgro, 2025). The software analyzes the entire image, identifies predefined color classes (e.g., sky blue, foliage green, human skin tones), and aligns corrections with the host application's color management settings.

iCorrect EditLab operates in four sequential stages:

1. Neutral tone balancing: Identifies mid-gray regions to eliminate color casts;
2. White/black point detection: Sets dynamic range endpoints;
3. Saturation, contrast, and brightness adjustment;
4. Natural color restoration: Recalibrates individual hues to reflect real-world appearance.

4. Data Fusion

A critical challenge lies in processing and fusing data collected by a swarm of UAVs. Different drones may capture varying measurements or images of the same field segment, necessitating reconciliation and conflict resolution.

First, high-accuracy monitoring requires integrating heterogeneous data sources: RGB imagery, multispectral data, LiDAR point clouds, and thermal imaging. Such data fusion significantly enhances weed detection accuracy. Studies confirm that combining spectral, textural, and thermal features yields superior classification performance compared to single-modality approaches (FourWeekMBA, 2025; Monteiro, Santos, 2022).

Second, even homogeneous data (e.g., visible-spectrum photographs from multiple drones) exhibit overlapping regions that must be seamlessly stitched. Generating consistent orthomosaics and vegetation maps from partially overlapping images is essential to avoid gaps or duplicate counting of the same plants.

5. Image Recognition via Artificial Intelligence

Object detection in drone-captured imagery is framed as a classification problem within an AI system. Solving it requires a pre-assembled image database of regional flora, partitioned into training and validation sets. A neural network is then trained on this dataset to classify plant species in new, incoming images.

Since ground-truth labels (correct species identifications) are available for training samples, this constitutes a supervised learning task. The goal is to assign each detected plant to its correct taxonomic class. Unrecognized species – those absent from the training set – may be flagged as "unknown." Accumulation of numerous such cases would necessitate model retraining with expanded data.

The machine learning (Malinowski et al., 2025) pipeline for plant classification is illustrated in (Figure 6).

By aggregating observations from the drone swarm and classifying detected vegetation, a detailed spatial map of invasive species distribution and density can be constructed. This enables targeted intervention strategies – ranging from precision herbicide application to localized mechanical removal – optimizing resource use and ecological impact.

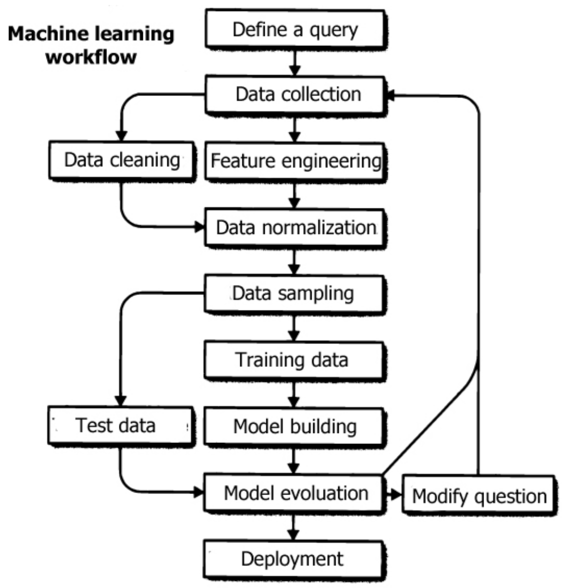

Fig. 6. Stages of the machine learning process

6. Advantages of Drone Swarm Monitoring

Compared to conventional field inspection methods, agricultural drone swarms offer the following advantages:

1. Rapid area coverage: Depending on model, a single drone can monitor 2–6 hectares in 10–20 minutes. Swarm deployment parallelizes this process, drastically reducing total inspection time.
2. Operation in complex terrain: High maneuverability and terrain-following sensors enable obstacle avoidance and effective monitoring on slopes, wetlands, and other inaccessible areas where tractors or personnel cannot operate.
3. Geospatial precision: GPS-enabled data ensures accurate mapping and repeatable monitoring.
4. All-weather and day/night operability: Equipped with appropriate sensors (e.g., thermal, NIR), drones function independently of lighting or meteorological conditions.
5. Cost efficiency: UAVs significantly reduce expenditures on ground machinery, fuel, and labor.
6. Multifunctionality: Modern drones support advanced features such as waypoint marking, mission pause/resume, multi-payload coordination, and centralized task management.

Agronomists traditionally face significant time and labor demands in routine field inspections. The integration of NDVI (Normalized Difference Vegetation Index) maps enables real-time vegetation monitoring, highlighting priority zones for ground verification.

NDVI quantifies vegetation presence and health by analyzing reflected light in visible and near-infrared (NIR) bands (Li, 2009). Chlorophyll-rich, healthy plants strongly absorb red light (used in photosynthesis) and reflect NIR due to intact cellular structure. Stressed or sparse vegetation exhibits the opposite pattern. Thus, NDVI serves as a proxy for crop vigor.

However, NDVI indicates that a problem exists – not why. Season-long NDVI trend analysis is essential for accurate diagnosis.

NDVI data is collected via satellites or UAVs equipped with NIR cameras, operating from orbital altitudes down to ~700 m. This enables high-resolution, actionable field maps.

The data acquisition workflow includes:

1. Equipment calibration for specific crops and conditions;
2. Placement of ground control points;
3. Aerial image capture;
4. Georeferencing of all field segments.

Post-processing yields detailed vegetation health maps, empowering agronomists to prioritize interventions and forecast yields.

Sentinel-2 satellite imagery provides NDVI at 10 m/pixel resolution, enabling fine-scale analysis – superior to other optical indices limited to 20 m/pixel. Nevertheless, NDVI has limitations: its sensitivity declines at high canopy densities, and persistent cloud cover can degrade data quality, necessitating complementary radar or UAV-based sensing.

Moreover, NDVI performs poorly in fields with low vegetation cover or during early growth stages. In such cases, the MSAVI (Modified Soil-Adjusted Vegetation Index) offers a robust alternative. MSAVI accounts for soil background effects (color, moisture), making it particularly effective during early season monitoring when soil is still visible between sparse seedlings.

6. Conclusion

The deployment of agricultural drone swarms for monitoring crop fields substantially enhances agronomic efficiency. By automating visual inspection, enabling precise weed detection, and leveraging AI-driven analytics, this approach significantly boosts labor productivity in agriculture while supporting sustainable, data-driven decision-making.

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