Intelligent UAV-UGV-SN-based system for monitoring and preventing forest fires

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Abstract
The article discusses the principles of development and application of an integrated system for monitoring and preventing forest fires using unmanned aerial vehicles (UAVs), ground autonomous systems (UGVs), and stationary sensor networks (SNs). The proposed system architecture provides for the prompt collection, processing, and analysis of environmental data using modern neural network algorithms and clustering methods. Suggested integrated approach combines the mobility of unmanned (UAV-UGV) platforms with continuous parameters monitoring using SNs. The integrated UAV-UGV-SN-based system allows for timely detection of threats, forecasting the spread of fires and coordinating measures to eliminate them. The results of the study demonstrate an increase in the efficiency of emergency response and a reduction in economic and environmental losses.

Keywords
forest fires, monitoring, UAV, UGV, sensor networks, neural networks, forecasting, integrated systems

1. Introduction

1.1. Motivation

Forest fires have become one of the most serious environmental and social problems of our time. Every year they destroy millions of hectares of forest, causing significant damage to nature, the economy and society [1]. In the conditions of climate change, the risks of fires are only increasing, which requires the development of new effective methods for their detection and elimination. This is confirmed by studies that compare the effectiveness of different fire detection algorithms [2, 3].

An additional factor that increases the risk of fires is military operations, which can cause forest fires due to artillery shelling, air strikes or arson. Forests often become the scene of hostilities, which makes it difficult to control the situation and eliminate fires by traditional means. In such conditions, the use of unmanned systems for monitoring and fighting fires is critically important to reduce threats to both ecosystems and the civilian population.

Traditional methods of monitoring forest fires are often not fast and effective enough. Therefore, it is important to integrate mobile and stationary subsystems for timely warning, detection of fires and their effective elimination. A mobile subsystem of unmanned aerial vehicles (UAVs) and ground-based (UGVs) allows for rapid data collection from hard-to-reach areas, which increases the accuracy and speed of response [4]. Unmanned aerial vehicles provide quick detection of fire sources, while ground-based robotic platforms can operate in conditions dangerous to people, performing localization and primary extinguishing of fires. A stationary subsystem based on sensor networks (SN) provides continuous monitoring of the environment, which allows predicting the possibility of ignition and promptly responding to threats [5].

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The combination of mobile and stationary technologies allows creating a comprehensive system for monitoring and combating forest fires, which combines the flexibility of mobile devices with the reliability of stationary sensors.

1.2. State of the art

An analysis of modern research on the use of sensor networks, UAVs, and ground-based systems for forest fire monitoring covers a wide range of approaches to early detection, forecasting, and response.

In [6], the use of UAVs with thermal imagers and multispectral sensors for the rapid detection of fire sources is considered. In [7], the deployment of sensor networks is studied with an emphasis on energy saving and reliability of data transmission in hard-to-reach areas. In [8], the integration of sensor data with AI methods for predicting the spread of fires is analyzed, which improves the accuracy of risk assessment.

The works [9, 10] are devoted to modeling fire behavior taking into account vegetation, terrain, and weather conditions, offering numerical methods for assessing the effectiveness of fire prevention measures. In [11], remote sensing methods for automatic fire detection using satellite images are considered. The study [12] focuses on hardware solutions and communication interfaces between sensors. In [13], the integration of UAVs and ground-based robots (UGVs) for comprehensive fire detection and suppression, including communication between platforms, is analyzed. In [4], an early detection system based on wireless sensor networks using ZigBee is described. In [14], an overview of integrated monitoring systems combining data from sensors, UAVs, and satellites is proposed.

The study [15] shows that AI methods, including clustering, allow not only to analyze current data, but also to take into account historical trends, forming dynamic risk maps. This facilitates preventive measures and optimization of resources for fire fighting.

The analyzed works consider individual aspects of the use of UAV, UGV and SN for detecting, forecasting and extinguishing forest fires. However, there is no holistic integration of mobile (UAV, UGV) and stationary (SN) subsystems using neural networks to predict fire spread and coordinate actions in real time. This gap leads to delays in making operational decisions and does not allow for predictive prevention. Therefore, our research is aimed at developing and testing a single framework that will combine the advantages of unmanned platforms with continuous SN monitoring and powerful algorithms based on neural networks to increase the efficiency of fire risk management and reduce economic and environmental losses.

1.3. Purpose, objectives and methodology

The purpose of this article is to design and prototype an integrated forest-fire monitoring and suppression system that combines unmanned aerial vehicles (UAVs), unmanned ground vehicles (UGVs) and stationary sensor networks (SNs) in order to improve early detection, accurate forecasting and coordinated response. The research methodology is based on a comprehensive analysis of modern technologies, modeling and development of prototypes of an integrated system considering application neural networks for forecasting forest fires.

Research objectives and stages are the following:

- **Justification of the architecture of the integrated UAV-UGV-SN system**. To substantiate the architecture of an integrated UAV–UGV–SN environment that ensures synchronous interaction of subsystems for maximum coverage of the territory and prompt response. (section 2).
- **Formation of a set of scenarios for the use and interaction of the subsystems**. To develop scenarios of the system operation at different stages (planning, pre-fire monitoring, fire detection and extinguishing, post-fire recovery) with the definition of the functions of UAV, UGV and SN and the role of neural networks. (section 3).
- **Development of neural network technology to support monitoring**. Justification of the general algorithm of the neural network, description of the features of its architecture and

mechanisms of integration into the general system for automatic analysis of data from sensors and visual streams (section 4).

- **Experiment.** conduct an analytical experiment that will allow you to assess the potential of clustering and identify weaknesses for further improvements (section 5).
- **Discussion of the solutions and future research steps.** Discuss the results of the analysis and identify areas for further research (SN expansion, satellite data integration, adaptive models, etc.). (section 6).

2. Architecture of the integrated UAV-UGV-SN system

This section is devoted to a detailed description of the architecture of an integrated system combining UAV and UGV and a stationary sensor network (SN) for forest fire prediction, monitoring and suppression. The main goal is to provide prediction, rapid fire detection, operational data collection and effective response to emergencies through the synchronous operation of all system components.

2.1. General concept of an integrated system

The integrated system is built on the principle of interaction of three main subsystems.

The first subsystem is a UAV swarm. It performs the role of rapid visual data collection and creation of a communication channel between individual elements of the system. Fire extinguishing is also possible. The effectiveness of using UAVs in such systems has been demonstrated in works on cooperative search and tracking [16, 17]. The next subsystem is a UGV swarm. The main task of this subsystem is to localize and extinguish fires. The last subsystem is SN sensor networks. They are deployed in high-risk areas and provide continuous monitoring of environmental parameters (temperature, humidity, smoke and gas concentration). Data from the sensors are sent to the central station for primary processing and analysis.

This combined architecture allows using the advantages of both approaches: continuous monitoring of stationary sensors and mobility and efficiency of unmanned aerial vehicles, which significantly increases the effectiveness of responding to threats. Figure 1 shows a general architecture diagram.

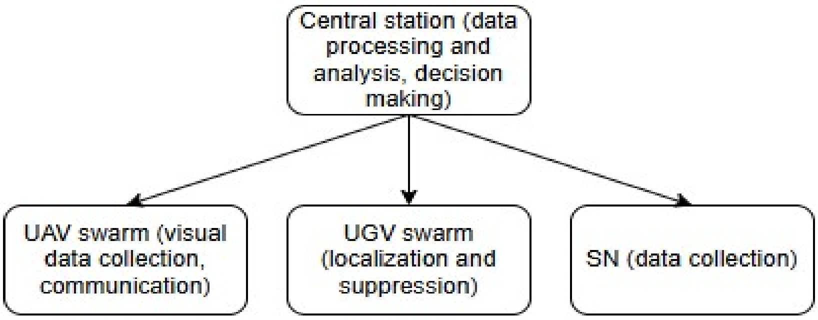

Figure 1: General system architecture: the central station performs data processing, analysis and decision making, while three subsystems operate in parallel—(1) the UAV swarm for visual data collection and communication relay, (2) the UGV swarm for fire localization and suppression, and (3) the SN (sensor network) for continuous environmental data collection (temperature, humidity, smoke, gas concentrations).

2.2. System components

The main components of the system play a key role in ensuring comprehensive monitoring and rapid response to forest fires. The system is based on the integration of several elements that interact with each other to achieve high accuracy of fire detection and fire suppression efficiency.

First, the stationary sensor network consists of various devices, such as thermal and infrared cameras, smoke detectors, gas analyzers, meteorological, acoustic and multispectral sensors, which are installed in critical areas with a high risk of fire. These sensors continuously collect data on temperature, humidity, smoke and gas concentrations, which allows for real-time detection of anomalies that may indicate the onset of a fire. The application of multispectral processing for fire monitoring has been described in detail [18].

Secondly, unmanned aerial vehicles are equipped with high-precision optical, infrared and thermal imaging cameras to provide the possibility of detailed aerial photography and video surveillance of the territories where changes from the operation of the sensor network were recorded. Due to their high mobility, UAVs quickly cover large areas, verifying warning signals, and also creating a stable communication channel between various components of the system.

Thirdly, unmanned ground vehicles play a crucial role in fire localization and immediate response. Equipped with means for transporting fire extinguishing materials and equipment for forming fire protection strips, UGVs carry out a detailed survey of the scene, which allows isolating and localizing the fire.

The central control station, as the core of the system, receives all data, processes them using powerful neural network algorithms and analyzes the information obtained to build dynamic risk maps and predict the development of the fire. Thus, thanks to the comprehensive integration of the sensor network, UAV, UGV, communication unit and central control station, the system is able to detect fires in a timely manner, respond promptly and coordinate fire extinguishing measures, which significantly contributes to reducing economic and environmental losses.

2.3. Interaction and reliability of subsystems

The integrated system operates through a continuous cycle of monitoring, analysis, and response, ensuring timely detection and suppression of forest fires while maintaining an up-to-date risk map. A stationary sensor network continuously collects data on temperature, humidity, smoke, and gas concentration in critical areas. When anomalies are detected, data is transmitted via secure wireless channels to the central station, where it is combined with historical trends to enhance prediction accuracy [19, 20].

Based on this analysis, UAVs are deployed for aerial imaging and thermal surveillance, transmitting real-time data back to verify fire alarms and update the risk map. If the threat is confirmed, UGVs are dispatched for ground inspection, fire isolation, and initial suppression efforts. Throughout the process, sensor networks continue collecting and transmitting data, allowing real-time monitoring and prediction of fire development for coordinated response actions.

A key feature of the system is reliable communication between UAVs, UGVs, and the central station. UAVs act as relay nodes, ensuring uninterrupted data transmission even in complex terrain or high network loads. To enhance reliability, the system employs redundant communication channels, combining primary wireless networks with backup options to maintain stable operation in adverse conditions [21]. A modular architecture enables easy expansion by integrating new sensors and mobile platforms without disrupting performance.

Autonomy is achieved through embedded neural network algorithms capable of making local decisions when communication with the central station is lost. These algorithms analyze sensor data, predict fire progression, and initiate response measures independently. Additionally, self-monitoring mechanisms continuously assess equipment status, detect failures, and switch to backup modes to prevent data loss and malfunctions.

This integrated approach ensures continuous monitoring, real-time response, and dynamic risk assessment, minimizing economic and environmental damage from forest fires.

2.4. Advantages of integrated architecture

The UAV-UGV-SN-based system combines smart data handling, unmanned mobility, and accurate environmental checks to cover all bases in fire monitoring, prediction, and suppression. Its standout feature is efficiency: a real-time sensor network works in tandem with UAVs for quick aerial surveys and UGVs handling ground tasks, cutting down detection and reaction times when compared to older methods [22].

Another plus is its all-round monitoring capability. By merging inputs from sensors, drones, and ground vehicles, the system creates a full picture of the situation and keeps false alarms to a minimum. The risk map is continuously updated using both live and historical data, which lets AI algorithms spot high-risk zones by looking at past fire events, weather trends, and vegetation shifts. This helps kick off preventive actions before problems really start.

Flexibility is a key characteristic as well. The system can run on its own through neural networks or in a mixed mode with human oversight, adapting to different situations. Its robust design includes backup communication paths and even lets UAVs serve as relay stations, ensuring steady data flow even in tricky terrains.

The modular setup makes it easy to expand, whether by adding more sensors, new platforms, or updated AI models without major changes to the infrastructure. This adaptability means the system stays efficient over time, allowing for continual tech upgrades.

In short, this integrated approach allows not only detecting and extinguishing fires, butpredicting and preventing them. By leveraging both real-time and historical data, the system refines fire prevention methods, cuts down on economic and environmental damage, and ensures prompt responses before fires get out of hand.

3. System application scenarios

3.1. Classification of scenarios

This section discusses the main scenarios for the application of the integrated UAV-UGV-SN system for monitoring, forecasting and extinguishing forest fires. Each scenario covers a specific sequence of actions and defines the functions of unmanned aerial vehicles (UAV), ground robotic platforms (UGV / forestry machines) and stationary sensor networks (SN). The results that can be achieved through the synergy of these components are highlighted separately. Table 1 provides an example of eight basic scenarios that can be modified or expanded depending on the specifics of the landscape, climatic conditions or management goals.

Table 1

Application scenarios of the integrated UAV-UGV-SN system

№	Scenarios	Functions	Neural network	Result
Sc1	AI-based fire forecasting and prediction	**UAV:** data collection on temperature, humidity, wind speed, recognition, etc. **UGV/Forest machine:** ground analysis. **SN:** analysis of current and historical data to build a risk map and predict fire occurrence.	**UAV:** processes images from cameras to detect early signs of fire and anomalies **UGV/Forest machine:** analyzes data from ground sensors and conducts comparative analysis of local indicators **SN:** clusters data, builds a dynamic risk map based on current and historical values	Proactive warning, identification of high-risk areas and timely detection of potential fires
Sc2	Early detection of fires	**UAV:** aerial photography with thermal imagers and smoke detectors. **UGV/Forest machine:** ground-based parameter verification. **SN:** capturing anomalies in climate data.	**UAV:** performs visual anomaly recognition, identifies potential fire locations. **UGV/Forest machine:** analyzes local data and confirms or refutes the signal received from the UAV. **SN:** detects sudden changes in temperature or other parameters indicating fire	Reduction of response time and prompt verification of fire

Sc3	Autonomous fire extinguishing	**UAV:** determining optimal points for water/foam discharge. **UGV/Forest machine:** creating firebreaks, ground extinguishing. **SN:** monitoring temperature changes.	**UAV:** calculates optimal points and routes based on image and thermal data analysis **UGV/Forest machine:** monitors the effectiveness of local extinguishing measures and responds to changing situations **SN:** continuously analyzes temperature indicators to correct the extinguishing strategy	Optimize resource usage and quickly extinguish fires
Sc4	Recovery after fire	**UAV:** seed scattering for forest regeneration. **UGV/Forest machine:** care for planted seedlings, watering, fertilizing. **SN:** soil and moisture monitoring.	**UAV:** analyzes the condition of the terrain using images, identifies areas with the most damage **UGV/Forest machine:** monitors the condition of plants and the need for additional care **SN:** evaluates ecological indicators to adjust restoration measures	Accelerated ecosystem recovery and fire mitigation

3.2. Scenario description

Scenario Sc1: AI-based fire forecasting and prediction

This scenario integrates sensor data, historical climate records, and past fire incidents. Neural networks identify patterns signaling increased fire risk, as demonstrated in [23]. UAVs regularly gather temperature, humidity, and wind data, while sensor networks compare them with historical trends for early hazard detection. This enables timely preventive measures like enhanced monitoring or forest moistening. Neural networks operate at different subsystem levels: UAVs analyze images and video for fire signs, ground systems assess local data against typical indicators, and sensor networks use clustering models to create dynamic risk maps and predict potential fires.

Scenario Sc2: Early fire detection

In normal mode, the sensors show stable readings, but if a sudden temperature jump or smoke appears, the system immediately gives an alarm signal. Drones with thermal cameras quickly inspect the situation from above, and ground equipment double-checks the data. Neural networks help to recognize anomalies: deviations are seen from the air, and from the ground they are confirmed or denied. This approach allows for a quick response and minimization of damage.

Scenario Sc3: Autonomous fire extinguishing

Once a fire is confirmed, the system automatically switches to extinguishing mode. Ground robots then determine the best points for applying water or extinguishing agents, taking into account wind and terrain features. Meanwhile, flying drones focus on monitoring the fire, relaying real-time information between the ground drones and the central station. Sensors continuously track temperature changes to enable prompt adjustments, and neural networks optimize routes, analyze thermal images, and assess the efficiency of the extinguishing efforts in real time.

Scenario Sc4: Recovery after fire

After the extinguishing fire, the restoration phase begins. Drones scatter seeds over the damaged area, and ground devices water, fertilize, and monitor plant growth. Sensors record the condition of the soil and the level of moisture, and neural networks analyze the resulting images to determine which areas need the most attention. This comprehensive approach allows the ecosystem to gradually return its lost functions.

4. Neural network technologies for integrated system

This section describes the use of neural network technologies to support forest fire monitoring, taking into account the tasks of clustering data obtained from sensors located in different parts of the land. The use of such approaches allows not only to quickly analyze current environmental indicators, but also to classify areas by risk level, identifying patterns that may indicate an increased probability of fire. The use of deep neural networks to detect fire threats is described in [24], and the use of clustering methods is described in [25].

Neural network algorithms are able to effectively process large amounts of data obtained from stationary sensors located in different parts of the forest. Due to the ability to detect complex patterns and anomalies, neural networks allow building dynamic risk maps, predicting possible fires, and supporting the process of making operational decisions. One of the important stages is data clustering, which allows grouping areas with similar characteristics and identifying those of them where the fire risk is highest.

4.1. Architecture of a neural network system with clustering

The neural network system for monitoring forest fire risks is based on the integration of various technologies for collecting, processing, and analyzing data from sensor devices (SN), unmanned aerial vehicles (UAV), ground autonomous systems (UGV), and other sources. The main task of the system is not only to collect and analyze current environmental indicators, but also to cluster the obtained data to predict the risk of fires and ensure prompt response.

The architecture of this system consists of several key components (Figure 2):

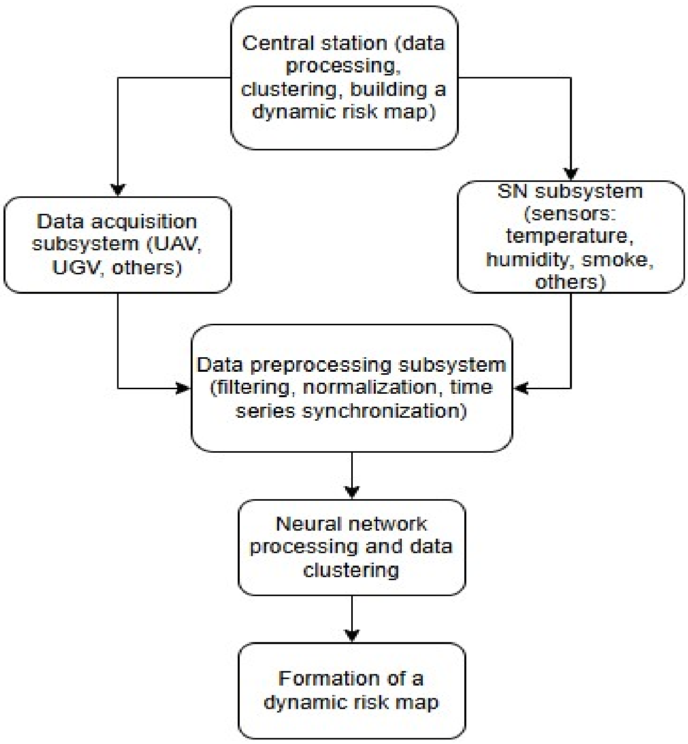

Figure 2: Architecture of the neural network processing and clustering subsystem. (1) Data collection subsystem gathering temperature, humidity and etc. readings from stationary SN, optical and thermal imagery from UAVs, and environmental scans from UGVs; (2) Data preprocessing subsystem performing noise filtering, normalization, anomaly removal, missing-value imputation and time-series synchronization; (3) Neural network feature extraction; (4) Generation of a dynamic risk map with real-time color-coded threat levels; (5) Fire prediction module analyzing temporal trends; (6) Continuous model retraining for adaptive parameter tuning.

- **Data collection subsystem:** All data on the condition of forest areas comes from a distributed network of sensors installed on the ground, as well as from unmanned aerial vehicles and ground-based autonomous robots.
- **Data preprocessing subsystem:** Data received from sensors has different formats and often contains noise, anomalies or unreliable values. Therefore, before further analysis, the following will be performed: data filtering and normalization, anomaly removal and restoration of lost values, aggregation and synchronization of time series for correct processing.
- **Neural network processing and data clustering:** After pre-processing, the data is fed to a neural network model. This will extract features, which will automatically extract relevant features, such as the correlation between humidity levels, temperature, and gas concentrations. And using clustering for risk analysis, forest areas are automatically divided into risk groups.
- **Dynamic risk map generation:** After clustering, the system will build an interactive risk map that displays all forest areas with specified threat levels. This map is updated in real time and is the main tool for making operational decisions.
- **Fire prediction system:** A fire prediction system will operate based on historical data and current indicators. It will analyze changes in indicators over time and neural networks to determine the probability of fires in specific regions in the near future. This will allow for early implementation of preventive measures (for example, moistening areas or installing additional fire barriers).
- **Automatic learning and adaptation of the neural network:** Another feature of the system will be its ability to self-learn. The neural network will continuously receive new data and update its clustering and forecasting algorithms to improve the accuracy of risk analysis and increase the efficiency of the system in the long term.

The architecture of a neural network system with clustering provides for the efficient collection, analysis, and processing of environmental data, the creation of risk maps, and the prediction of fire occurrence. This architecture will allow for the response to threats and the implementation of preventive measures to significantly reduce the likelihood of large-scale fires and minimize their consequences.

4.2. Algorithm of using neural networks with clustering

In the future, our forest fire monitoring and forecasting system will combine collection, analysis and rapid response using a multi-layered approach to data processing. First, a map will be created that collects of: average temperature, humidity and other climate characteristics. This map will become a baseline for assessing the long-term condition of the area.

In parallel, data will be collected in real time using sensors installed throughout the territory. These devices will continuously record current environmental parameters – temperature, humidity, pressure and other important indicators, which will allow timely detection of changes in the environmental situation. All data will be displayed on a separate map demonstrating current conditions in each region (Figure 3).

The use of neural networks in a future forest fire monitoring system will be particularly feasible and effective when applied to data collected from relatively small forest patches. As described above, we will collect two main types of data for each target area: historical annual climate records and real-time sensor readings. This dual-data approach will provide a robust dataset that reflects both long-term trends and immediate environmental changes, capturing subtle shifts that may precede fire outbreaks. By combining these datasets, our neural network will perform a detailed cluster analysis to estimate the likelihood of a fire occurring in a given forest patch. The network will analyze the data to identify patterns and anomalies that may indicate increased fire risk. For example, an area that has historically experienced moderate temperatures but later exhibits a sudden temperature spike coupled with a rapid drop in humidity will be marked as a high-risk area (yellow) on our dynamic risk map. This localised analysis will not only refine the overall risk assessment across the forest, but will also allow us to implement targeted preventative measures and allocate resources more efficiently. In addition, the system will continuously monitor environmental conditions in real time, providing regular updates that allow us to quickly respond to any emerging threats.

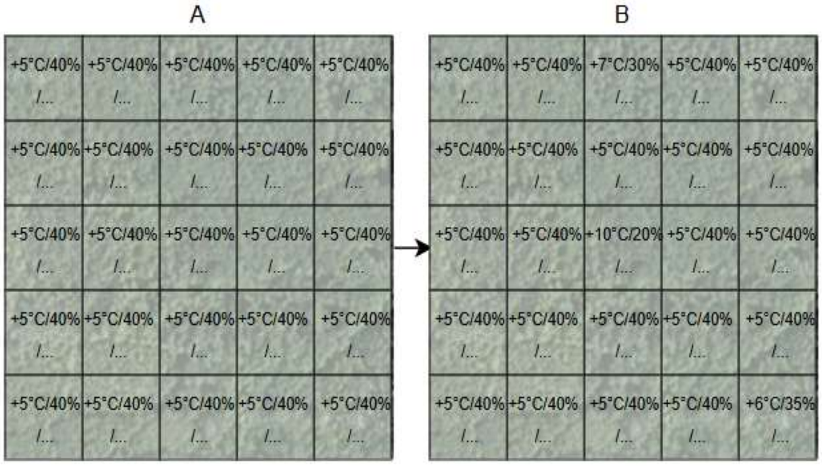

Figure 3: Wildfire risk maps: (A) — map based on annual climate data, (B) — map based on current sensor readings.

As the neural network learns and adapts over time, its predictive accuracy will improve, allowing it to adjust to changing environmental patterns and further improve early warning capabilities. This adaptive quality ensures that even minor changes in microclimate are taken into account, making the monitoring system both proactive and resilient.

Overall, using neural networks in this way will not only be practical, but also extremely valuable, ensuring that even the smallest, most vulnerable parts of the forest receive ongoing attention. This approach is set to significantly improve our ability to predict, prevent and respond to fires, thereby reducing damage and increasing the overall reliability of our fire management system.

Based on accumulated annual data and indicators, the neural network will perform cluster analysis and create a dynamic fire risk map in real time. This map will be continuously updated and will demonstrate the current threat level using color coding: green will mean a stable condition, yellow - increased risk, and red - signs of a fire. This approach will allow not only to visually assess the situation, but also to quickly respond to the occurrence of dangerous conditions.

When a yellow signal appears indicating a potential threat (for example, a sharp increase in temperature or a decrease in humidity detected by sensors), the system will automatically send a drone to inspect the corresponding area in detail. The drone will fly out to confirm or deny the presence of danger, providing additional information through video and photo data (Figure 4).

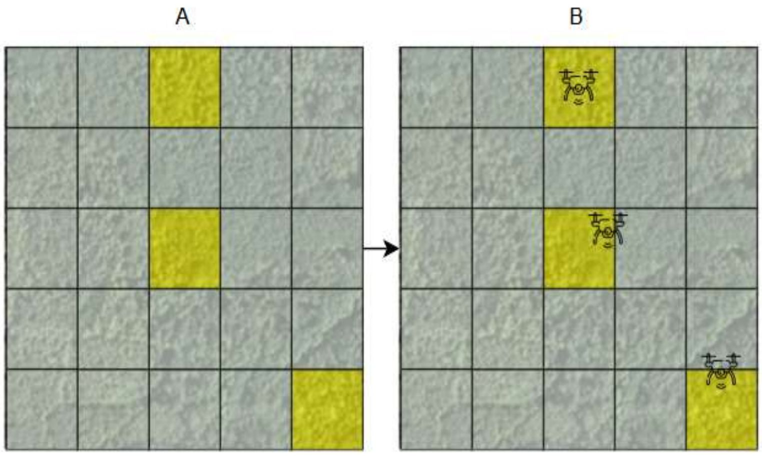

Figure 4: Drone zone inspection stage: (A) — yellow preliminary risk areas, (B) — confirmed high-risk areas.

If, after checking the drone, the information confirms that the fire has already started or is in its early stages, the system will immediately activate the extinguishing mode. At this point, the neural network will update the zone status on the map, turning it red, which will signal the need for immediate intervention. Both air and ground assets will be used simultaneously: drones for aerial monitoring and applying primary extinguishing measures, as well as ground robots (UGV), which will be sent to carry out local fire extinguishing measures (Figure 5).

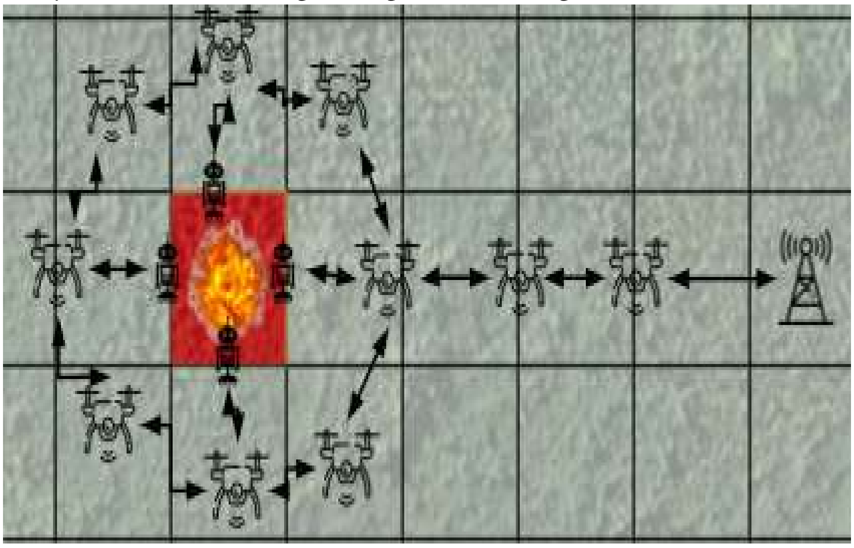

Figure 5: Map update during extinguishing: black arrows show data exchange between UAV, UGV and ground station. Red areas dynamically expand or contract based on thermal imaging data and sensor readings.

Thus, the integrated system will provide a comprehensive approach to forest fire prevention and suppression in the future. First, it will analyze annual and current data to assess the state of the territory, then create a dynamic risk map, promptly respond to anomalies using drone inspection and, if a fire is confirmed, activate a comprehensive extinguishing system involving both air and ground assets. This mechanism will significantly improve the efficiency of monitoring, reduce response time and minimize damage from fires, ensuring reliable risk management in forest areas.

4.3. Advantages of using clustering

In the future, clustering in neural network systems will play a key role in increasing the efficiency of monitoring, preventing and eliminating the consequences of forest fires. The use of clustering methods will allow not only to structure large volumes of data, but also to optimize decision-making based on the local characteristics of each region. Also among the advantages are local accuracy (grouping areas with similar characteristics allows more accurately identifying regions (where there is an increased risk of fire) and optimizing resources (clustering results help to optimally allocate resources for response, focusing on the most risky areas).

5. Experiment

The purpose of the section is to demonstrate the neural network clustering algorithm on synthetic data, to decompose the steps of calculating metrics (Precision, Recall, F1-score), and to show how to use simple mathematical calculations to assess the quality of the forecast of fire risk areas.

5.1. Problem statement and data

Let us take a set of 12,000 observations, each of which is described by five features: temperature (°C), humidity (%), smoke concentration (arbitrary units), wind speed (m/s), and dryness index (arbitrary scale 0–100). The observations are distributed across three risk classes: low (6,000 samples, 50%), medium (3,600 samples, 30%), and high (2,400 samples, 20%). The algorithm consists of two stages: first, MLP feature extraction, where each five-dimensional vector is passed through a sequence of layers 5 ⟶ 32 ⟶ 16 ⟶ 8 to obtain an 8-dimensional representation, and then the k-means method (k = 3) is applied to these 8-dimensional vectors to assign each observation to one of three clusters.

To assess the effectiveness of clustering, consider the confusion matrix, which shows how many observations of each real class were assigned by the algorithm to each of the predicted classes in Table 2.

Table 2
Frequency of Special Characters

	Predicted: low	Predicted: medium	Predicted: high
Realistic: low	5 400	300	300
Realistic: medium	200	3 300	500
Realistic: high	100	150	1 850

In this matrix, for the class "low" we have TP = 5400 (the number of truly low-risk observations classified correctly), FN = 300 + 300 = 600 (low-risk observations incorrectly classified as medium and high), and FP = 200 + 100 = 300 (observations from other classes incorrectly classified as low-risk). Similarly, FN and FP are determined for the classes "medium" and "high", after which the classification quality indicators for each of the three classes are calculated using the formulas Precision, Recall, and F1 score.

5.2. Formulas and calculations

For each class i (ℓ – low, m – medium, v – high), standard metrics are used:

$$Precision_i = \frac{TP_i}{TP_i + \sum_{j\neq i} \quad FP_{j\to i}}, \tag{1}$$

$$Recall_i = \frac{TP_i}{TP_i + \sum_{j\neq i} \quad FN_{j\to i}}, \tag{2}$$

$$F1_i = 2\frac{Precision_i \cdot Recall_i}{Precision_i + Recall_i} \tag{3}$$

where TP_i (True Positives) denotes the number of observations that belong to class i and were classified into it correctly. $FP_{i\to j}$ (False Positives) is the number of elements from class j that the algorithm mistakenly assigned to class i. $FN_{i\to j}$ (False Negatives) is the number of elements of class i that were mistakenly assigned to other classes j≠i.

Formula (1) gives Precision — the ratio of correctly predicted positive cases to all predicted positives. A high Precision value means that there are few false positives among the predicted observations of class i.

Formula (2) calculates Recall — the ratio of correctly predicted positives to the total number of true positive cases. Recall shows the ability of the algorithm to find all samples in class i.

The combined F1-score metric in formula (3) is the harmonic mean of Precision and Recall, providing an objective assessment of the balance between these two indicators.

For the "low" class (ℓ) from the discrepancy matrix we have:

$$TP_\ell = 5400, FP_{m\to\ell} = 200 + 100 = 300, FN_{\ell\to m} + FN_{\ell\to m} = 300 + 300 = 600 \tag{4}$$

Substituting these values into (1)–(3), we obtain:

$$Precision_\ell = \frac{5400}{5400 + 300} \approx 0.9474, Recall_\ell = \frac{5400}{5400 + 600} \approx 0.9000, F1_\ell \approx 0.9235 \tag{5}$$

After this, according to this example, we consider the same for the "medium" and "high" class. Now we can calculate the overall macro F1 score.

$$macro\ F1 = \frac{F1_\ell + F1_m + F1_v}{3} = \frac{0.9235 + 0.8513 + 0.7793}{3} \approx 0.8514 \tag{6}$$

As a result, we get table 3, which shows all the results.

Table 3
Summary table of results

Risk class	Precision	Recall	F1-score
Low	0.9474	0.9	0.9235
Medium	0.88	0.825	0.8513
High	0.6981	0.8809	0.7793
Macro F1			**0.8514**

The example calculation for the "low" risk class (ℓ) shows how the combination of precision and completeness yields F1 ≈ 0.9235. This indicates that the algorithm is quite good at separating low-risk areas: only 600 out of 6,000 such areas were misclassified, while medium and high risks yielded 300 false positives.

For the "medium" class (m), Precision = 0.88 and Recall = 0.825 show that although the algorithm is able to detect most of the medium-risk observations, some of them (700) still fall into other classes. F1 ≈ 0.8513 demonstrates a balanced result, but indicates the possibility of further refinement.

High risk (v) turned out to be the most problematic: with Recall ≈ 0.88 the module is able to find most of the critical points, but due to a significant number of false positives (800) Precision drops to ≈ 0.6981, which leads to F1 ≈ 0.7793. This indicates that the algorithm needs to improve in terms of accuracy of recognition of the most dangerous zones.

Finally, Macro-F1 (7) of ≈ 0.8514 generalizes the results across all three classes and allows comparing the quality of different models with each other regardless of the imbalance in the data. In our case, a value above 0.85 indicates a generally good ability of the model to classify risk zones, but draws attention to the need for optimization specifically for high-risk cases.

5.3. Interpretation and conclusions

Interpretation of the obtained results indicates that the clustering algorithm with a combination of MLP feature extraction and k-means demonstrates a sufficiently high ability to separate zones of different risk levels. In particular, the "low risk" class received the highest F1-score (~0.9235), which indicates the minimum number of false positives and misses in this category — only 600 out of 6000 truly low-risk samples were classified incorrectly, and the number of false positives was 300. The "medium risk" class demonstrated an F1-score of ≈0.8513, which indicates a satisfactory balance between Precision (0.88) and Recall (0.825), but 700 observations still ended up outside their group, which may be due to the proximity of the parameters of these zones to the boundary values. The algorithm has the greatest difficulty in classifying "high-risk" areas: although Recall for this class (~0.8809) shows that most critical cases are detected, the high level of false positives (800) reduces Precision to ~0.6981 and leads to an F1-score of ≈0.7793. This indicates the need to refine the boundary conditions of the clusters or introduce additional features to increase the accuracy of recognizing the most dangerous areas. The Macro-F1 indicator of ≈0.8514 summarizes the effectiveness of the algorithm in conditions of class imbalance and serves as a benchmark for comparison with alternative approaches: a value above 0.85 indicates good model quality, but the identified weaknesses require additional experiments and possible adjustment of the network architecture or clustering parameters.

6. Discussion of the solutions and future research steps

Comparison of the obtained results with traditional clustering methods indicates significant advantages of the proposed combination of MLP-feature extraction and k-means: if pure k-means in similar studies demonstrates Macro-F1 of about 0.81 [25], then the addition of nonlinear vector processing increases this indicator to 0.85. This increase is explained by the fact that MLP allows better separation of clusters in the transformed feature space, increasing the clarity of the boundaries between classes. At the same time, the analysis of the discrepancy matrix revealed a systemic problem with the recognition of the most critical — high-risk — class: Recall for this group is approximately 0.88 (i.e., the algorithm finds most of the true “red zones”), but a large number of false positive classifications (~800) leads to a decrease in Precision to ~0.70. This imbalance between sensitivity and accuracy is repeated in many works on environmental data clustering, where close to threshold values of features make it difficult to clearly separate critical and non-critical observations.

To address this limitation, it is advisable to apply several approaches: first, to conduct detailed normalization and standardization of input features, taking into account their mutual correlation; second, to expand the set of parameters by adding a complex fire hazard index (FWI), which integrates several risk factors; third, to consider hybrid models that combine clustering with threshold detectors that can instantly respond to extreme changes in individual features.

It should be noted that the main limitation of this study is the use of synthetic data without testing on real sensor networks and field tests. Although analytical calculations allow us to quickly assess the potential of the algorithm and identify its “weak points”, experiments on UAV/UGV equipment in different climatic zones with real data from sensors are necessary to confirm its practical value.

In the future, the integration of satellite and meteorological data can bring significant benefits, which will allow us to cover larger areas and improve the spatio-temporal consistency of forecasts. In addition, the development of adaptive algorithms that will automatically adjust the number of clusters depending on seasonal and regional features, as well as the implementation of a feedback system from operators for online model updates, will contribute to increasing accuracy and reliability in real-world applications. Overall, the discussion confirms the validity of the chosen approach and outlines clear paths for its further improvement and scaling.

7. Conclusions

The main contribution of this research is the development of the architecture of an integrated (UAV+UGV+SN)-based forest fire monitoring system, the definition of scenarios for its use and the implementation of neural network support for each stage of work. The integration of mobile unmanned vehicles (UAVs and UGVs) with stationary sensor networks allows significantly increasing the efficiency of fire detection and response. Thanks to continuous monitoring of the environment and the use of modern neural network technologies for data clustering and analysis, the system is able to form dynamic risk maps that take into account both current indicators and historical trends. This allows accurately identifying areas of increased risk and implementing preventive measures to reduce economic and environmental losses.

Of particular importance is the use of an integrated approach that combines the advantages of mobile systems - efficiency, the ability to cover hard-to-reach areas, safe performance of work in combat zones - with the reliability of stationary sensor networks. In regions where military operations create additional threats, the proposed system can effectively provide early fire detection, rapid response and forecasting of fire outbreaks, which is key to protecting both ecosystems and the civilian population.

Further research should be aimed at improving data analysis and clustering algorithms, expanding the sensor network, and integrating additional sources of information, including satellite data and data from public organizations. As a result of the implementation of such innovative technologies, it is possible to create autonomous, adaptive systems capable of providing a comprehensive approach to monitoring, forecasting and eliminating forest fires, which will help reduce the scale of losses and improve the ecological situation.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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