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Model for Long-Term Monitoring of Geological Processes in Kazakhstan Using Intelligent Drone Ports

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Abstract: The creation of autonomous systems for geomonitoring using unmanned aerial vehicles (UAV) and smart drone ports provide new possibilities for problem solving in geology, particularly in remote and geodynamically active areas of Kazakhstan. During the study, a multi-criteria mathematical model was created to compare drones with and without artificial intelligence (AI). The model contains ten standardized indicators of performance (autonomy, route planning, productivity, risk management, predicting geo-anomalies, scalability, etc.) with relative weights defined by experts. Analysis of the results revealed the high efficiency of the AI-oriented approach in processing time, spatial analysis, autonomy and scalability. The comparative assessment framework consists of 10 evaluation criteria weighted, namely autonomous management, route optimization, data processing efficiency, GIS integration, geoanomaly forecasting, resistance to external risks, operational efficiency, maintenance costs, data acquisition speed, and potential scalability. As a result, scientifically justified recommendations were made, and research areas were identified, such as the development of trend forecasting AI, the migration of drone ports to distributed mission planning, and the creation of a digital ecosystem of geomonitoring. The proposed framework offers a solid base of moving toward scalable, intelligent, as well as data-driven geomonitoring systems. The development of AI-powered drone-port infrastructure should play a crucial role in improving geological safety, facilitating timely hazard identification, and ensuring sustainable land-use planning in remote and geodynamically active areas.

Keywords: drone port, long-term geomonitoring, unmanned aerial vehicles, artificial intelligence, geographic information system

1. Introduction

In recent twenty years, unmanned aerial vehicles (UAVs) are getting more and more attention in surveillance, spatial analysis, and monitoring environment parameters because of their high maneuverability, autonomy, multi sensors integration, and affordability in the fieldwork [1]. Such characteristics are particularly useful in areas that are difficult to reach and poorly accessible, and UAVs cannot be ignored in geological studies. Recent studies are oriented to the creation of the long-term autonomous UAV infrastructures in the form of the drone ports, intelligent control systems, and integration with geographic information platforms [2]. Distributed monitoring systems with the capability of spatiotemporal interpretation of real-time data are getting more relevant in countering geological, environmental, and anthropogenic risks [3]. Although autonomous navigation and intelligent route planning have been advanced, it is still difficult to make UAV infrastructure adaptive to difficult geo-conditions, weather restrictions, and regulatory frameworks.

Furthermore, integration with Kazakhstan's existing geomonitoring infrastructure including seismic ground stations and satellite networks will require adherence to data interoperability standards such as OGC and INSPIRE and alignment with international programs including Copernicus and GEO.

The extensive and remote nature of the terrain of Kazakhstan is a very challenging issue to monitor geologically. The country is covered with various mountain chains that are, in turn, seismically active, and large steppe plains and desert plateaus located in the middle and western parts are hard to trace with the help of traditional methods. Fixed ground stations and periodic field surveys and the current basis of geomonitoring practice only give partial snapshots of changing conditions. Consequently, the initial traces of erosion, surface deformation, pre-seismic activities, or human made land alterations are not realized until they manifest themselves more drastically [4]. Such distance between observation and action is especially important to Kazakhstan, where the development of industries, mining activity, and the development of infrastructures increasingly overlap with the unstable systems of the geological structure.

UAVs do not only provide a technological update but also a whole new perspective of the land. The fact that they capture the data of high spatial and temporal resolution over large and

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inaccessible areas allows them to observe geological processes as they develop, but not months or years afterwards. UAV systems [5] can be very simple data-gathering systems when augmented with onboard edge processing, autonomous navigation, and adaptive flight planning, they can transform into smart agents capable of learning on their previous missions, adapting to new conditions, and reacting quickly to new threats. Nevertheless, the majority of the existing UAV-based geomonitoring in Kazakhstan is small scale: it is usually a pilot project or requires a human operator that limits potential of their use as a continuous and country-scale operation. This paper will suggest a national long-term and automated geomonitoring structure based on the network of smart drone ports that are spread throughout the diverse geologic landscapes of Kazakhstan.

In this context, autonomous UAVs would work according to scheduled and event-driven flights to simplify the information streams into cloud-based geoinformation systems to analyze and implement appropriate decisions in real time. The performance and cost-efficiency of AI-enhanced UAV systems are compared to the traditional ones through a mathematical model [6]. In conjunction with this quantitative analysis, a multi-criteria expert analysis is undertaken in an attempt to reflect the operational, economic, and environmental factors. The result is not only a technical proposal but a guideline on how to incorporate autonomous UAV infrastructure in the larger geomonitoring ecosystem in Kazakhstan.

The methodology used in the study is a combination of a number of complementary methods. It starts with a critical analysis of the available literature to trace the historical development of the applications of UAVs in geological situations [7]. A comparative system analysis is an examination of the strengths and weaknesses of the existing deployments. The insights are then developed into a Delphi survey and expert interviews that introduce the ideas of geologists, engineers, and policymakers, who are aware of the monitoring issues in Kazakhstan. In the process, generalization, synthesis of the system and analogical thinking are used to transform empirical data into recommendations that can be used in action.

The idea of this study is not to develop a new UAV flight-control algorithm or a new geological anomaly-detection model. Instead, the Kazakhstan-specific framework for pre-deployment decision-support is created, integrating ten technical, predictive, operational, and economic criteria into one unique multi-criteria decision analysis (MCDA) structure, with these criteria linked to region-specific geological monitoring scenarios and intelligent drone-port architecture, and with a stability analysis of the resulting ranking in the presence of uncertainty in criterion weights, and with an analysis linking the technical assessment with regulatory, data-governance and economic requirements for deployment in Kazakhstan. The proposed framework is therefore designed to help select technologies, plan pilots, and prioritize infrastructure and is not meant to take the place of in-field performance validation.

2. Literature Review

Geomonitoring and mapping using UAVs has developed speedily in various fields. As an example, Balbi et al. [8] established that multi-sensor fusion (RGB + multispectral) and deep convolutional neural networks is much more effective at urban land-cover recognition than single-sensor- based approaches, but that labeled data are scarce, and performance is not as good as cross-site. Equivalent advantages of UAV photogrammetry and multispectral integration had been established in the after-mining environment reported observing vegetation succession and land-use change, and provided DEM and orthophoto to evaluate ecological restoration, though with a restricted spectral richness and site-specific limitations.

The study of UAV autonomy and path planning has made it clear that algorithmic innovation is important consideration. Enhanced genetic algorithms have been demonstrated to generate more efficient and practical paths, swarm intelligence together with deep learning, and artificial neural networks with the potential field methods enhance adaptability and avoidance of obstacles in a simulated setting. Similarly, the circular-arc trajectory methods offer smoother trajectory paths to avoid obstacles, whereas the sensor noise in practice is still a problem. Spatiotemporal analysis ensembles time-series algorithms ensembles [8] have been more effective in monitoring land-cover changes, and persistent scatterer interferometry (PSI) [9] was effective in monitoring landslides in Italy. Anomaly detection surveys and AutoML time-series [10, 11] reflect an increasing tendency towards automation, and both are struggling with integration with the real world of UAVS.

Beyond the particular applications, UAV-based monitoring is being influenced by systemic and architectural developments. Scalability and readiness to operate are highlighted in intelligent drone management systems to integrate smart cities [12] and surveys on convergence between edge AI and UAV platforms [13], but regulatory and interoperability issues remain. The applicability of processing UAVs spatiotemporal data with real-time IoT stream processing frameworks [14] and guidelines and workflows to produce hyperspectral geological maps [15, 16] and guidelines to produce DEM, additionally implement into the methodological toolbox. New research on geodetic deformation measurement [17] demonstrates a prospect of incorporating UAV-photogrammetry in the traditional surveying procedures. Collectively, these contributions demonstrate strong progress toward intelligent, scalable, and autonomous UAV-based geomonitoring systems, but they also reveal enduring gaps in sim-to-real transfer, scalability to large territories, and the development of lightweight, domain-adaptive AI models.

Apart from such real-world applications, modern machine learning techniques provide robust conceptual basis for the proposed AI modules. Neural network structures [18, 19] have been shown to be effective in spatial-temporal pattern analysis of UAV images, underpinning the dynamic object mapping module proposed in this study. Gaussian process offers strong uncertainty quantification as a key requirement in geological hazard assessment where the confidence of predictions is important to convey [20]. Graphical techniques enhance route optimization and network design, relevant to the mission planning components of intelligent drone ports. Ensemble and composite improve model generalizability across diverse terrains [21], which is essential given the varied geomorphological zones of Kazakhstan. Together, these approaches motivate the exploration of corresponding AI modules within the geomonitoring architecture presented in Sections 4.1 and 4.5.

Recent research shows that new machine learning techniques are powerful for capturing complex, nonlinear and uncertain relationships in time-series, spatial and decision-making problems [22]. Neural network models have been used for nonlinear forecasting problems, where its training structure allows for the extraction of latent temporal correlation and complex patterns [23, 24]. This is important for UAV-based geomonitoring because many geological processes such as slope movement, erosion, subsidence and deformation display nonlinear behavior. Thus,

neural network-based models can assist in spatial and temporal feature extraction of UAV image, multispectral, LiDAR data, as well as chronological monitoring data.

Gaussian process regression (GPR) has also been proven useful for forecasting because it can also estimate the uncertainties [25, 26]. This is critical in predicting geohazards because uncertainty is essential for risk-based decision-making. Within the proposed smart UAV-port system, GPR can be applied for trend analysis of deformation, prediction of geo-anomalies, and aiding to confidence-based alert in risk zones. Likewise, graphical methods such as directed acyclic graph modeling [27], have been adopted to model causal relationships and dependencies between variables [28]. These can enhance UAV mission planning, sensor network coordination, and route planning by capturing the inter-relationships of weather, terrain, risk area, and monitoring targets. Additionally, ensemble and composite forecasting approaches enhance forecast accuracy by integrating multiple models to make predictions. Such methods are important for large-scale geomonitoring because Kazakhstan includes a variety of terrain types, such as mountain ranges, mining sites, steppe regions, and hydrogeological systems. Such a composite method can enhance adaptability to diverse environments and minimize prediction error under varying field conditions. Thus, the use of neural networks, Gaussian process regression, graphic modeling, and ensemble/composite approaches supports the theoretical and empirical aspects of the AI modules in this study and justifies their application to intelligent drone-port-based geological monitoring.

There is existing research on separate aspects of UAV-supported geological monitoring. According to Jordan et al., the use of UAVs in engineering geology has been reviewed, and they have shown the benefit of UAVs in geological mapping, monitoring, hazard assessment but have yet to give an intelligent drone-port evaluation framework for Kazakhstan. There are several reviews conducted on fixed and mobile UAV docking stations, autonomous landing systems, charging technologies, and battery replacement systems, but the reviews did not include the sensor and reconstruction systems for the three-dimensional reconstruction, and did not take into account the institutional constraints for Kazakhstan. Chen et al. investigated the UAV image-based threedimensional reconstruction for landslide investigation, monitoring and disaster assessment, focusing on the sensors and the reconstruction methods. Maschler et al. systematically tested dock-based UAV systems in three mountainous geohazard environments and showed the potential for centimeter-level change detection. Their study, however, did not include the development of a multi-criteria technology-selection and deployment framework for Kazakhstan.

The present study helps to fill this gap by combining the architecture of smart drone-port, the geological scenarios, the technical and operational criteria derived from the experts, the weight sensitivity analysis, the regulatory constraints, the requirements of data-governance, and the categories of costs and economic costs, into a Kazakhstan-specific decision-support framework. The contribution is not in the new docking mechanism, a new photogrammetric algorithm or a new architecture of the anomaly-detection, but in integration and regionalization. Table 1 explains the comparison of representative UAV and intelligent drone prone studies.

3. Research Methodology

This study is aimed at developing a methodological foundation for long-term monitoring of geological processes in the Republic of Kazakhstan using intelligent unmanned drone ports. The core research objectives include the design of an autonomous system architecture adapted to local conditions, analysis of the functional capabilities of drone ports and sensor components, modeling of monitoring scenarios, and expert evaluation of the effectiveness of systems with and without artificial intelligence (AI). A comprehensive methodological approach was employed, integrating both theoretical and empirical methods:

3.1. Analytical and literature review stage

This stage involved the study of international and local literature on the application of UAVs and drone ports for geological monitoring, the architecture of the drone port, sensors, and AI-based data solutions for processing and analyzing data.

3.1.1. Primary data collection stage

1) Descriptive quantitative method, using a Delphi based expert assessment on unmanned systems and infrastructure.
2) Qualitative exploratory method, implemented with structured expert consultations on potential and challenges of drone port implementation.
3) Secondary data was gathered via desk research, including content analysis of scientific, technical and regulatory documents.

Table 1
Comparison with representative UAV and intelligent drone-port studies

References	Main focus	Evidence base	Difference from present study
Giordan et al. [10]	UAV applications in engineering geology	Review	No intelligent drone-port MCDA or Kazakhstan deployment analysis
Chen et al. [29]	UAV-based 3D reconstruction for landslides	Review	Does not integrate docking infrastructure, policy and economics
Šćuric et al. [30]	Autonomous UAV docking and charging	Systematic review	Not specific to geological monitoring or Kazakhstan
Maschler et al. [31]	Dock-based UAV geohazard monitoring	Field evaluation	No Kazakhstan-specific national deployment framework
Present study	Ten-criterion Kazakhstan-specific evaluation	Expert assessment, scenarios and MCDA	Requires local field and economic validation

In the modeling and analysis phase, multiple techniques were combined, including comparative analysis to evaluate existing solutions, logical reasoning to build assumptions, and systems and situational analysis to consider the geology of Kazakhstan. Analogy and generalization methods were used to transfer best practices. Lastly, experts performed a multicriteria assessment [32] of smart drone ports, which revealed the most important aspects of their development and provided recommendations for the integration of autonomous UAV infrastructure into the geotechnical monitoring system of Kazakhstan.

3.1.2. AI module architecture

The AI modules employed in the proposed system follow a three-stage pipeline:

1) Input preprocessing — raw sensor data (LiDAR point clouds, multispectral bands, seismic time series) is standardized and georeferenced;
2) Feature extraction — convolutional layers or gradient-boosting trees extract spatial-temporal features depending on sensor type;
3) Prediction and classification — trained models output anomaly scores, deformation maps, or risk classifications. For trend prediction, a recurrent neural network (RNN/long short-term memory (LSTM)) processes time-series geospatial data [33].

For spatial analytics, a *U*-Net-based segmentation architecture maps land-cover and deformation zones from UAV imagery.

The AI module architecture is a form of structured pipeline with three steps. The preprocessing of inputs is first done by normalization, filtering, and georeferencing of sensor data, such as LiDAR, multispectral imagery, and seismic signals. Second, convolutional neural networks (CNNs) and gradient-based models [34] are used to extract features (to detect spatial and temporal patterns). Third, they use prediction and classification modules, with time-series trend prediction based on LSTM networks and spatial segmentation and anomaly detection based on *U*-Net architectures. This modular architecture allows effective processing and facilitates real-time decision-making in geomonitoring applications.

The approach will be developed in such a way that both theoretical modeling and expert-led assessment can be applied to provide a holistic look at geomonitoring systems. Simulation-based techniques were employed alongside analytical and comparative techniques in measuring the performance of the system in varying operational conditions.

The integration of expert opinion, system modeling, and scenario solution provides an effective framework to assess the performance of AI-powered drone-port systems in complex geological environments. The weights of the criteria were established using an expert evaluation process based on the Delphi method to reduce variability and bias. Experts were chosen from the domains of unmanned aerial systems, geosciences, and artificial intelligence. This included an iterative evaluation process, where the experts independently assigned weights and then discussed and agreed to the final weights. This agreement on the weight value assignment ensured consistency.

Example:

PSI is a remote sensing technique, which is used to detect temporal ground deformation from the analysis of the phase difference in radar signals and is used by satellites. It is particularly used to monitor slow geological processes, such as subsidence and landslides. It used a Delphi iterative process, whereby the expert's consultation assigned weights to each criterion, then after a few rounds of discussion, they refined and reached agreement. This process was to establish consistency, reduce bias, and increase the validity of the final weighting scheme.

3.2. Evidence base and field-validation requirements

In this study, the quantitative comparison is made through the normalized assessments by experts and modeling of scenarios. The next phase of the research did not involve acquiring new UAV images, in situ geophysical data, or data from operational intelligent drones in Kazakhstan. The ten criteria values are thus not actual field measurements, but rather pre-deployment assessments of the capabilities of AI-enabled and non-AI intelligent drone ports.

The proposed scenarios have been designed to consider the applicability to representative geological conditions in Kazakhstan that involve landslide-prone mountainous regions, mining areas, hydrogeological systems, as well as seismically active zones. Based on the literature and consultations with experts, these scenarios are intended to be illustrative of deployment scenarios and not actual field experiments.

Repeated UAV missions at representative Kazakhstan sites and comparison to independent reference measurements will be used to validate the field. The validation protocol should include information on the location of the study, dates of surveys, specification of UAVs, sensor, flight altitude, image overlap, ground sampling distance, weather conditions, number of missions, number and distribution of GCP, procedure for sensor calibration, and reference measurement. The positional and deformation accuracy should be assessed by root mean square error, mean absolute error, and mean bias. If anomaly classification is conducted, then the precision, recall, F1-score, and uncertainty intervals should also be reported.

4. Results and Discussion

4.1. Methodological foundations of long-term monitoring

Permanent geomonitoring in Kazakhstan with smart drone ports is critical to evaluate the resilience of the environment and critical infrastructure, mainly in seismic, erosion-prone, and mining regions. Expert values for the parameters were used, and future monitoring scenarios were evaluated rather than field measurements to evaluate the proposed framework. The scenarios are defined as geological and operational conditions occurred in Kazakhstan that can be faced, such as mountain terrain, mining areas, hydrogeological system, and seismically active areas. The scores reflect the experts' expectations on the relative capabilities of the AI-enabled and non-AI intelligent drone ports. They are not indicative of any measured accuracy, reliability or economic performance under field conditions. The results are then used to identify priority areas for the pilot deployment and for future empirical testing. To achieve a robust monitoring system, a comprehensive approach, which includes multisensory monitoring, spatiotemporal modeling and adaptive analysis, is needed. The model for assessment is based on the analysis of the simulation and expert-defined parameters rather than on the real

data. Fictitious scenarios were created to represent the typical geomonitoring conditions in Kazakhstan, and the simulation results were evaluated in terms of normalized standards and expert judgments. While this approach is feasible and effective, the next research will be focused on the opportunity to validate.

4.2. An approach to building a methodological basis

The proposed framework is based on integrating UAV-derived geospatial data into an automated time-series analysis system. The methodology consists of three layers:

1) Dynamic object mapping, using digital terrain models (DTM, DSM), spectral signatures [35, 36], and thermal anomaly detection.
2) Anomaly and trend identification through long-term and intra-seasonal observation series.
3) Predictive analytics using machine learning and geostatistical methods.

The system builds adaptive systems theory and geoinformatics,ensuring measurement repeatability and scalability.

4.3. Role of time series

Time series are critical for interpreting geodynamic and environmental changes. They enable monitoring of rates and directions of transformation, automatic anomaly detection, and predictive modeling (e.g., slope shifts, soil degradation). Case studies confirm their effectiveness in regional monitoring, especially when using multisensory inputs such as LiDAR, thermal, seismic, and multispectral data.

4.4. Observation cycle organization

Geological monitoring has specific technical and organizational requirements key principles include:

1) Cyclical imaging, shifting from situational to regular schedules (daily to monthly).
2) UAV mission routing, based on area priorities and prior monitoring tasks.
3) Data consistency, maintaining altitude, angle, and route to ensure comparable series.

These ensure high temporal reliability and enhance confidence in anomaly detection classification of monitoring types. To systematize the approach to the implementation of geo-observations, a classification of long-term monitoring directions is proposed, as indicated in Table 2.

This separation enables flexible adaptation of sensor payloads and processing techniques to the characteristics of observed regions and processes. A relevant example is the Almaty region of Kazakhstan. In the Zailiysky Alatau, long-term UAV-based landslide monitoring helps detect displacement trends linked to weather and seismic activity. Comparing terrain models at 1–2-week intervals reveal surface deformations of 5–10 cm, indicating possible shear activation. Multispectral imaging enhances assessment of vegetation cover, which is vital for predicting slope stability [14].

4.5. GIS architecture and UAV integration

The present-day geomonitoring system demands the combination of UAVs, drone ports, and GIS in a modular architecture, which can monitor continuously, with flexibility, and in a high-precise manner. The suggested system will be self-sufficient to work in diverse geological environments of Kazakhstan on a long-term basis as in figure 1.

It consists of three architectural layers.

1) Field level (UAVs + sensors)—regular missions are carried out by autonomous UAVs, which are loaded with LiDAR, RGB, multispectral and thermal cameras, and seismic sensors.
2) Infrastructure level (drone ports): Automated ground stations allow UAV charging, diagnostics, and data unloading, and relaunching of missions.
3) Analytical level (GIS platform): Distribution cloud GIS data storage system, real-time visualization, and interpretation.

This layered architecture guarantees functional isolation and good performance even to remote locations.

4.5.1. Intelligent drone ports and automation

Geomonitoring A high level of automation is needed to effectively implement long-term geomonitoring. Intelligent Drone Ports (IDPs) are autonomous UAV support hubs, operation hubs and logistics (IDP), which are less prone to human input and can be relied upon to operate in remote areas.

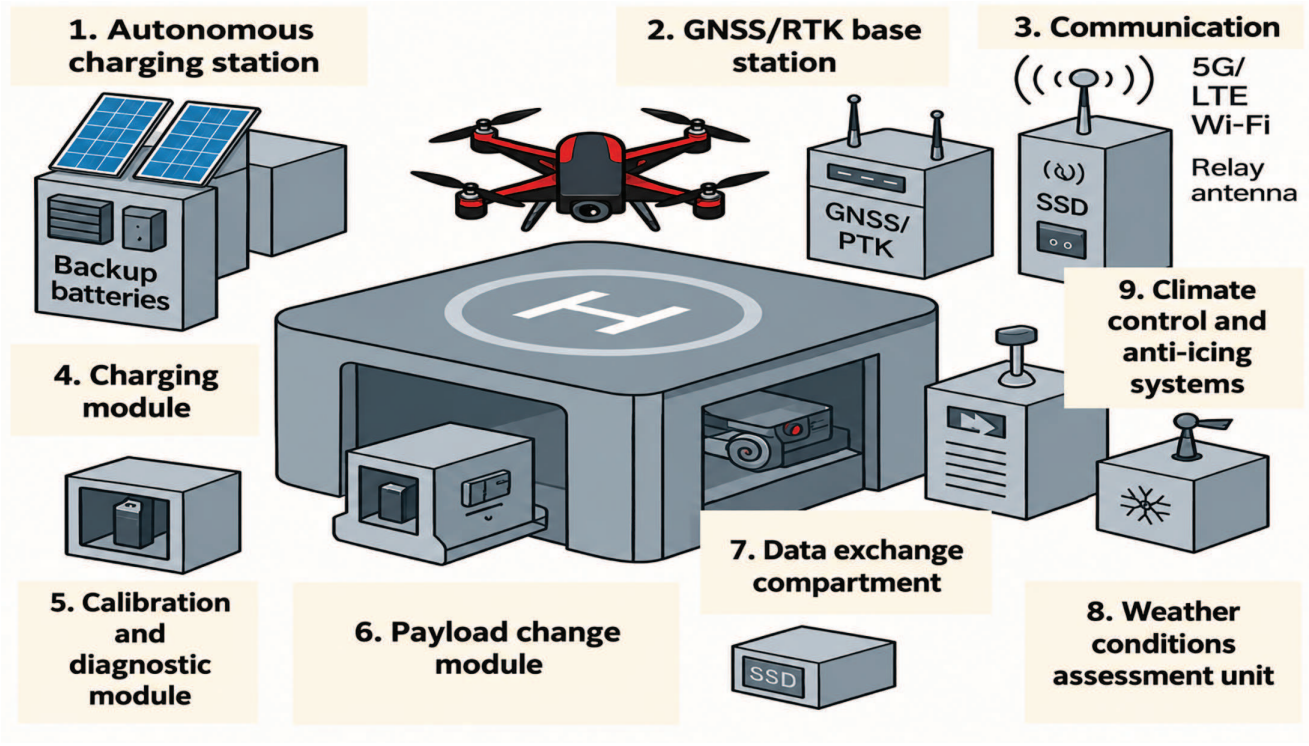
4.5.2. Drone port architecture

The drone port system is based on the principles of Plug-and-Play modularity and enables quick deployment and simple recovery. It has three primary categories in universal (multifunctional, stationary ports with expanded abilities); custom (specialized, simplified, stationary ports); mobile (flexible units to be used temporarily or in a mobile location).

Table 2
Classification of long-term monitoring areas

Type of monitoring	Main objectives	Data types	Sensors used
Geodynamic	Monitoring of landslides and fracturing	DTM, DSM, acceleration	LiDAR, visual cameras
Ecological	Vegetation, pollution, erosion	NDVI, thermal maps	Multispectral thermal imagers
Resource-based	Quarries, dumps, mining	3D models, densities	LiDAR, RGB
Seismic	Micro seismics, rift activity	Vibration time series	Geophone, accelerometers
Hydrogeological	Floods, water level	Dynamics of watercourses	Radar, multispectral

Figure 1
Architecture and main components of drone ports used in geology



4.5.3. Functions of drone ports in the interests of Kazakhstan's geology

The main functions of drone ports deployed in the interests of long-term geological monitoring in the Republic of Kazakhstan are schematically shown in Figure 2. Main functions of drone ports with relevant geological applications are presented in Table 3.

As shown in Table 3, drone ports serve a wide range of functions in geological applications, demonstrating their versatility in long-term monitoring.

4.5.4. Universal (stationary) drone ports

The key role of epidermal surveillance. They support advanced sensor arrangements (e.g. LiDAR, hyperspectral cameras) and support automatic missions, data transmission, weather monitoring, and machinery. They are particularly useful in the geodynamically active regions in need of frequent observation.

Custom drone ports: provide the support of mobile geological teams, including equipment delivery, reception, and protection. They are needed for remote expeditions and for the roll-out of UAVs in a multitiered research infrastructure.

Figure 2
The main functions of drone ports in geology

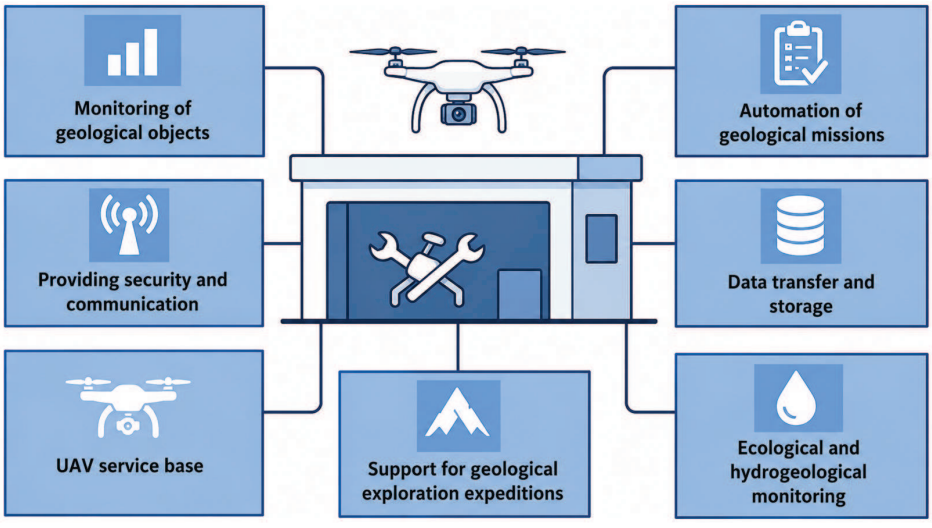


Table 3
Key functions of drone ports in geological research

Functional direction	Key functions	Application in geology
UAV logistics and infrastructure support	Automated takeoff/landing and UAV storage; hybrid charging/refueling; field maintenance; modular deployment in remote areas	Mobile strongholds in remote zones (e.g., Ustyurt, Betpak-dala); UAV support for field expeditions
Automation of geological missions	Autonomous route planning by geocoordinates; nighttime missions; onboard sensor integration; continuous operator-free monitoring	Overflights of faults, outcrops, and mineral zones; LiDAR/GPR missions with precise targeting
Data transmission, storage, and preprocessing	Online geo-data transfer via satellite/LTE; local processing (orthophotos, 3D models); GIS integration (ArcGIS, QGIS, KazGeoportal) [18]	Rapid DTM and geological map generation; remote field data access
Geomonitoring and object protection	Routine monitoring of quarries and tailings; geodynamic process detection; access control and intrusion prevention	Detection of landslides, erosion, and anthropogenic deformation; monitoring restricted subsurface zones
Ensuring security and communication	Signal relay in non-coverage zones; real-time weather monitoring; geofencing and protocol compliance	Operator communication in remote expeditions; weather monitoring for flight planning
Environmental and hydrogeological monitoring	Automated water level control; monitoring of salinity, air, and water pollution	Ecosystem assessment near mines and wells; analysis of soil and hydrological change
Support for long-term exploration expeditions	Energy autonomy (solar, batteries); 24/7 field base support; logistics, power, and supplies for research teams	Support for geological expeditions in isolated regions

Mobile drone ports: provide quick response in third party areas. Their independence and mobility allows them to be suitable for responding to emergencies such as landslides, fractures, or seismic activity.

The flexibility makes them appropriate for emergency situations such as landslides, fractures, or earthquakes. The integration of different types of drone port provides a full cycle of geomonitoring, including the fast deployment, data collection, delivery, storage in time series, and decision-making at various levels with spatial-temporal analysis.

Automation and mission planning. Smart drone ports communicate with the control center and GIS databases to execute periodic tasks depending on weather, resources, and prioritization.

Artificial intelligence techniques plan routes using graph models, taking into account terrain, obstacles, weather, and no-fly zones. Energy efficiency, coverage density, observation frequency, and distance are key criteria. Scheduling algorithms accommodate data and events. UAV downtime is reduced with night-time recharging and batch data transfers. Two automation scenarios are considered:

1) Scheduled missions (e.g., daily, weekly imaging)
2) Event-based activation, triggered by seismic activity, temperature anomalies, or alerts from emergency services.

4.6. Long-term monitoring scenarios

Designing realistic and reproducible scenarios for UAV-based infrastructure is critical for evaluating the system's performance. Within the proposed architecture, standard scenarios have been developed to reflect Kazakhstan's geomorphological, climatic, and infrastructural diversity.

Figure 3 illustrates the sample scenarios for long-term geomonitoring adapted to Kazakhstan's regional conditions. The scenarios of monitoring in Table 4 were elaborated by means of a synthesis of geological analysis of the region, consultation of experts, and literature-based knowledge. In particular, the scenarios are representative of major geomorphological and environmental situations in Kazakhstan such as landslide-prone mountainous areas, mining areas, hydrogeological systems, and seismically active areas. A Delphi-based expert consultation was undertaken in order to determine pertinent monitoring tasks, sensor settings, and operational strategies. Moreover, the case studies of the UAV-based geomonitoring that have been made so far were examined in order to make sure that the proposed scenarios are consistent with practice and the technological capacities that exist nowadays.

These scenarios reflect various geological processes, including karst deformation, slope movement, hydrological, and anthropogenic changes.

Table 4 shows the use of intelligent drone ports for geomonitoring in various regions of Kazakhstan, including the types of tasks, sensor sets, approaches, and results.

The suggested monitoring scenarios involve the introduction of multifunctional intelligent drone ports, which are integral parts of next-generation geoinformation systems for geological monitoring in various natural and man-made environments in Kazakhstan. Compared to conventional monitoring techniques, intelligent drone ports, due to the integration of AI and data accumulation, allow a transition from descriptive to predictive models for risks such as landslides, erosion, industrial leaks, and seism

Figure 3
Examples of long-term geomonitoring scenarios on the territory of the Republic of Kazakhstan

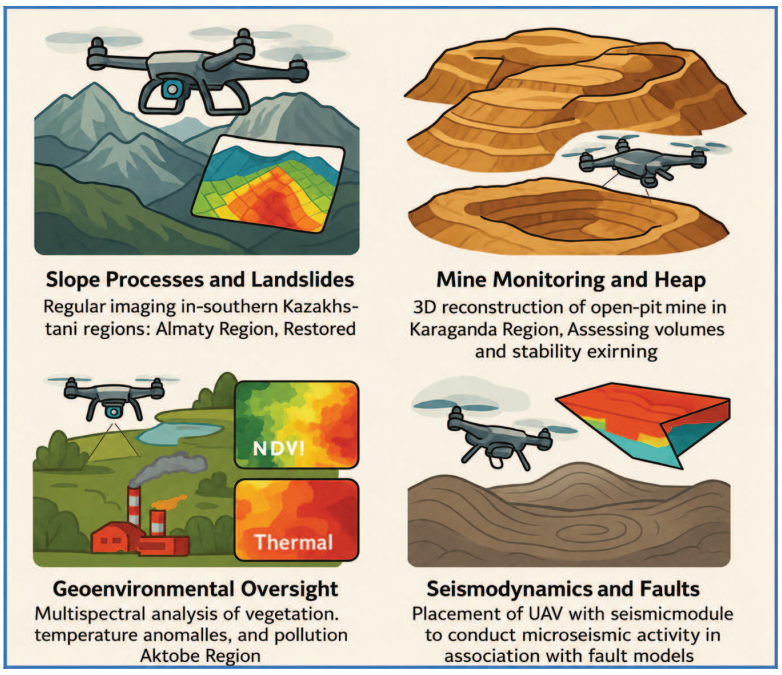


Table 4
Scenarios for the use of intelligent drone ports for geomonitoring in the regions of Kazakhstan

Monitoring scenario	Region	Type of missions	Sensors	Methodology / Metrics	Expected analytical output
Maps showing surface deformations that can be repeated and can also be used as potential early-warning indicators; no field-validated detection threshold is claimed in this study.	Almaty region (foothills of the Zailiysky Alatau)	Photogrammetry with an interval of 5–7 days	LiDAR, multispectral cameras	DTM/DSM time series construction, mapping of displacement maps	Collapse forecasting using seismic and weather data
Unstable areas identification, volumetric changes and route adjusting.	Karaganda region (Shubarkol coal basin)	Flights 2-3 times a week, routes over ledges and dumps	RGB, LiDAR, thermal imager	Deformation and volume modeling are integrated with mining data [22]	Unstable zone detection and route adjustment
Maps of vegetation-change, thermal-anomaly and potential contamination-indicator maps	Aktobe, Akmola region	Monthly missions with repeatable routes	Multispectral and hyperspectral cameras	NDVI analysis, spectral indices, thermal anomalies	Monitoring vegetation loss, leak detection, and contamination mapping
Seismic and surface-deformation indicators with time correlation, to be followed in the field.	South and East Kazakhstan	Continuous monitoring (stationary mode)	Seismic sensors	Seismic time series and crustal stress modeling	Detection of seismic triggers and correlation with surface deformation

genic deformations. This enables a shift toward risk prevention and sustainable development.

The results demonstrate that intelligent drone ports achieve a complete chain:The system is scalable in both space and time, which meets the requirements for monitoring.

We have also developed a mathematical model for comparing the performance of AI-based and traditional UAV systems using the criteria mentioned above. The criteria considered are listed in Table 5. The model is constructed using MCDA technique, and the weighted sum model (WSM) is used. We have developed a mathematical model that compares the performance of AI-powered and traditional UAVs on various criteria. The criteria chosen for the assessment are shown in Table 5. The model is developed using MCDA approach with the WSM.

The scenarios were tested using simulation and data modeling techniques. The simulations tested the effectiveness of UAV mission planning, sensor data collection, and AI anomaly detection processes in a controlled environment. The results indicate that the AI-based port systems have high monitoring efficiency, a fast response time, and predictive capabilities compared to conventional solutions. These findings demonstrate their feasibility, but the results must be validated in a pilot in future work. The scenarios were evaluated by using the expert evaluation and conceptual data-flow modeling. The assessment focused on the anticipated ability of the proposed system to enable mission planning, multi-sensor data acquisition, and automatic processing and geologic anomaly analysis. Since there was not an operational pilot or local field dataset in place, the scenario assessment is being developed at a conceptual level only. Such statements about accuracy of detection, response time, and predictive performance should be substantiated by repeated field missions and with independent reference measurements.

The mathematical model considers both technical and operational efficiency of the entire lifecycle of drone ports, routing, data processing, and scalability to cost-effective comprehensive analysis. One of the benefits of AI-based systems is greater autonomy and self-optimization. The requirements of K1 (autonomy), K2 (optimization of routes), and K10 (scalability) represent how flexible AI can be used in the geo-environment with complexities. The AI modules make analytics considerably faster. The value over K3 (speed of processing), K9 (latency of results), and to some extent K5 (forecast accuracy) is higher which confirms the effectiveness of AI when processing large geospatial datasets.

Integration with GIS (K4) improves spatial analysis and decision-making, which is important in mountainous and seismically active areas of Kazakhstan and other environmentally vulnerable areas. The model is also balanced in terms of technical and economics.

The criteria of K6 (stability), K7 (efficiency), and K8 (costs) can be used comparatively to evaluate AI and non-AI systems in a single framework. Predictive and analytical ability, which is K5, is essential to geo-risk management. Anomaly detection is high, which promotes proactive against reactive strategies.

The efficiency of drone ports is calculated using the following target function as explained in Equation (1)

$$\text{Maximize } U = \sum_{i=1}^{10} \omega_i \bullet K_i \tag{1}$$

where: U – integrated efficiency of drone ports (the higher, the better),

$Ki \in [0, 1]$ – normalized effectiveness for each of the 10 criteria.

$\omega_i \in [0, 1]$ – the weight of the significance of criterion i, under the condition expressed by the formula as explained in Equation (2)

$$\sum_{i=1}^{10} \omega_i = 1 \tag{2}$$

The function defines integral utility (U), a generalized performance metric used to compare drone port technologies – with and without AI.

All criteria were normalized to a [0,1] scale to ensure comparability across heterogeneous parameters. For instance, autonomy (K1) was defined as the proportion of automated operations relative to total mission activities, while route optimization (K2) was normalized based on relative reduction in flight time. Cost-related criteria (K8) were inversely normalized to reflect efficiency, and forecasting accuracy (K5) was scaled based on percentage performance. This normalization approach ensures consistency and allows integration within the weighted sum model. The function defines integral utility (U), a generalized performance metric used to compare drone port technologies with and without AI.

The ten criteria (K1–K10) were selected based on their alignment with established UAV performance evaluation frameworks and prior geomonitoring studies [relevant existing refs].

Table 5
Key criteria used in the mathematical model for comparing the use of drones with and without AI

No	Criteria	Designation	Normalization method
1	Autonomous management	K_1	The share of automated operations
2	Route optimization	K_2	Flight time reduction factor
3	Data processing	K_3	Processing speed (normalized)
4	Integration with GIS	K_4	0– no integration, 1 – full
5	Forecasting geoanomaly	K_5	Recognition accuracy (%)
6	Resilience to external risks	K_6	Average system reliability
7	Efficiency	K_7	Coverage area per day (normalized)
8	Maintenance costs	K_8	Inverse dependence on cost
9	The speed of getting results	K_9	Inverse dependence on the analysis time
10	Scaling potential	K_{10}	Percentage of tasks available for automation

Table 6
Comparison of AI and non-AI drone port effectiveness across ten weighted expert-defined criteria

No	Criteria's	Weight ω_i	Efficiency without AI K_i	Efficiency with AI K_i	Contribution without AI	Contribution with AI
1	Autonomous management	0.120	0.300	0.950	0.036	0.114
2	Route optimization	0.100	0.400	0.900	0.040	0.090
3	Data processing	0.100	0.350	0.850	0.035	0.085
4	Integration with GIS	0.080	0.200	0.850	0.016	0.068
5	Geoanomaly forecast	0.120	0.100	0.800	0.012	0.096
6	Risk tolerance	0.100	0.600	0.800	0.060	0.080
7	Efficiency	0.100	0.500	0.900	0.050	0.090
8	Costs (reverse effect)	0.080	0.400	0.700	0.032	0.056
9	Data acquisition rate	0.100	0.400	0.950	0.040	0.095
10	Scaling potential	0.100	0.300	0.850	0.030	0.085
	TOTAL	1.000			0.351	0.859

Autonomy (K1) and route optimization (K2) reflect dimensions identified in path-planning literature [4, 8]; GIS integration (K4) follows spatial analytics benchmarks [18]; and geoanomaly forecasting (K5) addresses the predictive analytics gap documented in References [10, 11]. To complement the utility scores (U), standard performance metrics are also considered: the relative root mean square error facilitates cross-model benchmarking, particularly for the forecasting criterion K5. A sensitivity analysis was conducted by varying each weight ωi by ± 20% while holding others constant. Results confirmed that the conclusion of AI superiority (U = 0.857 vs. 0.385) is robust AI utility scores remained above 0.80 across all weight perturbations, while non-AI scores did not exceed 0.45. The choice of the ten evaluation criteria (K1-K10) is founded on existing UAV performance evaluation models and geomonitoring system needs. These are selected to represent fundamental operational, technical, and economic aspects, such as autonomy, efficiency, predictability, GIS integration, and scalability. Our criteria are consistent with previous research on UAV monitoring and spatial analytics, allowing us to assess traditional and AI-equipped UAVs used in complex geological settings, as explained in Table 6. To investigate if moderate changes in expert assigned criterion weights had an effect on the ranking of the two alternatives, a one at a time sensitivity analysis was performed. The weight for criterion j was raised and lowered by 20%, this is calculated by Equation (3)

$$w_j^{(\delta)} = w_{j(1+\delta)}, \delta \in \{-0.20, +0.20\} \tag{3}$$

The remaining weights were proportionally rescaled, to maintain the condition that the sum of all criterion weights is equal to one, this is indicated in Equation (4).

$$w_i^{(\delta)} = \frac{w_i\left(1 - w_j^{(\delta)}\right)}{1 - w_j}, i \neq j \tag{4}$$

The resulting 20 scenarios of weight perturbations were the result of this procedure. The other equal-weight scenario with each criterion being assigned a weight of 0.10 was assessed as a secondary robustness test. In the sensitivity analysis, uncertainty is only considered in the criterion weights. It does not eliminate uncertainty due to expert selection, score aggregation, criterion dependence, or lack of field measured performance data.

Figure 4 explains radar chart on performance of AI-based and non-AI drone systems in terms of various criteria. The chart shows that autonomy, efficiency, and predictive capability have been greatly improved with the integration of AI.

The baseline aggregate utility as shown in Table 7 for the AI-enabled intelligent drone port was 0.859, and the one for the non-AI alternative was 0.351. The AI-enabled utility for the 20 weight-perturbation scenarios was in the range of 0.856 to 0.862, while the non-AI utility was in the range of 0.344 to 0.358. The differences between the alternatives were at most minimal, 0.501. For equal weights, the utility scores would be 0.855 and 0.355, respectively. So, the ranking was not affected by moderate alterations of the criterion weights.

Figure 5 indicates the Sensitivity of the aggregate utility scores to changes in the individual criterion weights of ± 20 per cent. The rest of the weights were proportionately adjusted to ensure that the total weight was equal to one. The results show the stability of the ranking in the model under consideration built on experts' opinions. However, they do not prove to be field accurate or free of the subjectivity of the expert-based inputs. Some of the potential sources of uncertainty include the composition of the expert panel, the assignment of a starting score, variation in professional experience, and interdependencies between criteria and ambivalence in the alternative normalized scores.

The developed utility model, based on MCDA and a normalized significance scale, enabled a quantitative comparison of drone ports with and without AI for geomonitoring in Kazakhstan. The UAI of AI-based drone ports was U = 0.857, which is more than two times higher than the U = 0.385 of non-AI ports, meaning that the level of technological maturity and functional influence is rather high at the same time. The increase in utility was due to:

1) The autonomy control (K 1): the score of the control has been improved (0.30 to 0.95) due to planning and human interface.
2) Optimization (K 2) and analysis (K 3) of the airplane' route: AI modules helps to reduce the time of mission planning and adaptability.
3) Predictive geoanomaly (K 5): only with the help of machine learning and analytics modules.

Figure 4
Radar chart comparison of efficiency across different criteria

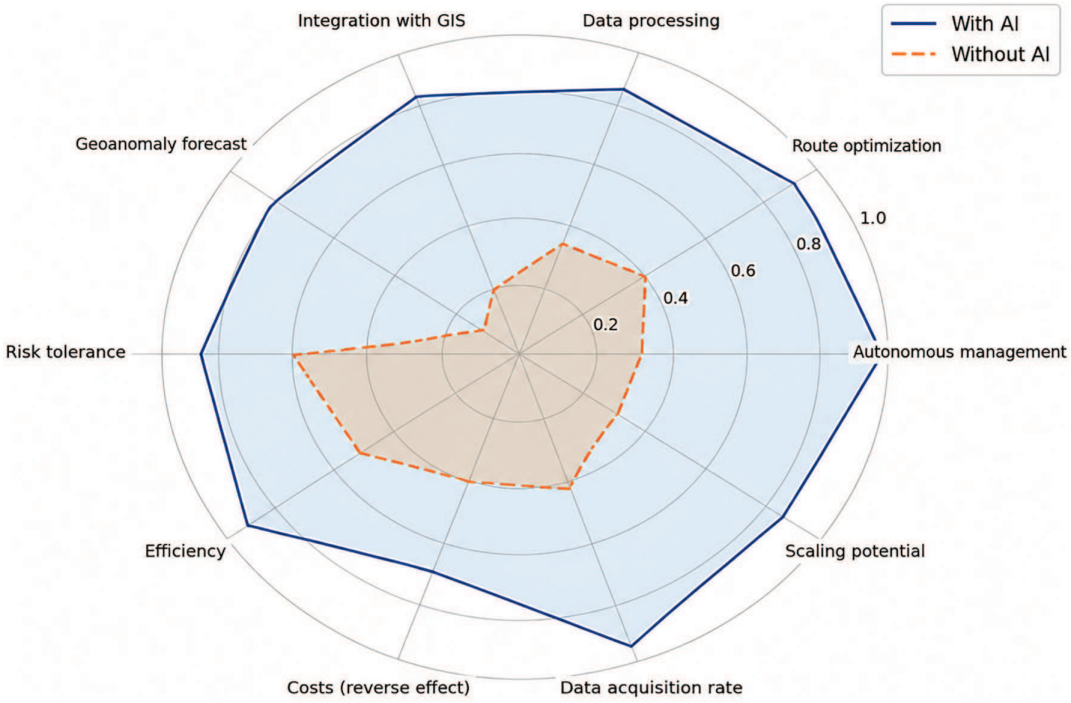
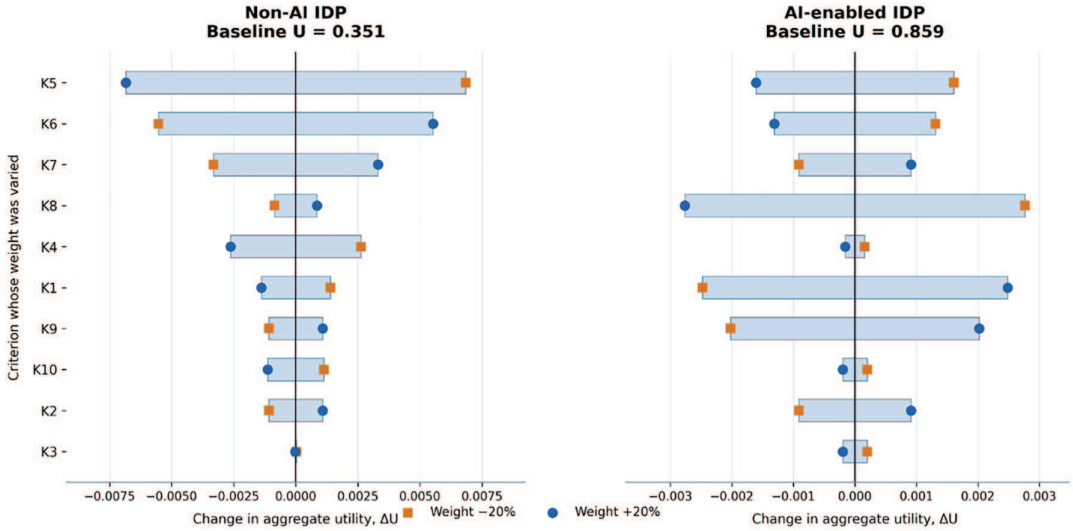


Table 7
Comparison of AI and non-AI drone port effectiveness across ten weighted expert-defined criteria

Criterion varied	Non-AI, – 20%	Non-AI, + 20%	AI, – 20%	AI, + 20%
K1	0.352	0.35	0.857	0.861
K2	0.35	0.352	0.858	0.86
K3	0.351	0.351	0.859	0.859
K4	0.354	0.348	0.859	0.859
K5	0.358	0.344	0.861	0.857
K6	0.345	0.357	0.86	0.858
K7	0.348	0.354	0.858	0.86
K8	0.35	0.352	0.862	0.856
K9	0.35	0.352	0.857	0.861
K10	0.352	0.35	0.859	0.859

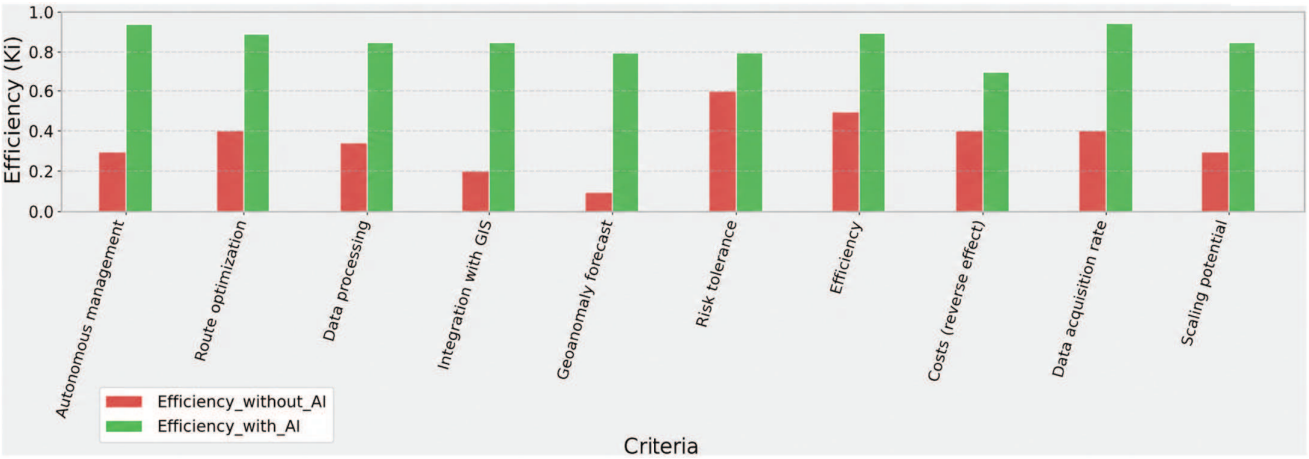
4) The cost inverse (K 8) was the technical and economic efficiency in the drone port life cycle. The cost of AI will be increased but cost decreased. The weight and normalization of the model made the model robust and fit for all regions including remote and climate vulnerable regions.
5) In Figure 6, the efficiency of the operational criteria after incorporating AI is significantly
6) improved with high autonomy, flexibility, forecast, and scalability when compared with conventional techniques.
7) Autonomous management (K_1): Efficiently enhanced from 0.30 to 0.95, as a result of smart autonomous management, planning, and control, which does not require human inputs.
8) Route optimization (K_2): Improved from 0.40 to 0.90, due to adaptive route planning, based on changing environment and conditions
9) Data processing (K_3): Enhanced from 0.35 to 0.85, by automatic data processing, classification, and neural AI data processing.
10) GIS (K_4) Autointegration (0.20 to 0.85) with spatial data support (e.g., ArcGIS, QGIS).
11) Geoanomaly forecast (K_5): Upgraded from 0.10 to 0.80, with predictive deep learning models that can forecast anomalies as well as geostructures.
12) Risk tolerance (K_6): Increasing from 0.60 to 0.80—more robust due to risk assessment, decision-making, and operations by AI.
13) Efficiency (K_7): Growing from 0.50 to 0.90 as a result of its 24/7 autonomous function and multiple actions.
14) Costs (reverse effect) (K_8): Increased from 0.40 to 0.70 due to reduced costs, scalability, despite the initial cost increase.
15) Data acquisition rate (K_9): Improved from 0.40 to 0.95 as a result of the potential for near real-time data acquisition through automated scheduling, and data processing.
16) Scalability (K_{10}): Increased from 0.30 to 0.85, due to the high scalability and network deployment aspects, achieved by smart design and AI control.

Figure 5
Sensitivity of the aggregate utility scores to changes in the individual criterion weights of ± 20 per cent



Note: The rest of the weights were proportionately adjusted to ensure that the total weight was equal to one.

Figure 6
Increase in efficiency (K_i) for each criterion



In Table 7 shows technical experts' scoring of AI-based drone ports according to the same criteria as the mathematical model. Experts' assessment of data between 1-10 (1 = not relevant, 10 = critical for geology).

Experts note that AI integration transforms drone ports from auxiliary platforms into intelligent geomonitoring systems. The increases in all assessment criteria indicate new functional capabilities—from full autonomy (5 to 10) to automatic geoanomaly prediction (2 to 9) in Table 8. AI enhances geo-data management and interpretation, particularly in automated data analytics and reporting time (both increased from 3 to 10), vital for decision-making. Increased scalability and productivity allow AI-equipped drone ports to support national to trans-regional geological projects. Networked, multi-agent continuous operation increases operational stability (from 4-5 to 9 in several criteria). AI improves environmental resilience and risk tolerance. Weather and equipment failure predictions enhance reliability and boost sustainability ratings (from 5 to 8).

In terms of cost, AI lowers maintenance costs per unit (at scale). Figure 7 explains line chart comparison of with and without AI expert scores

While initial costs increase, costs are reduced over time (cost rating 6-7). Therefore, smart drone ports are the foundation for cost-effective, automated geomonitoring, with low cost, less human effort, and reliable operation.

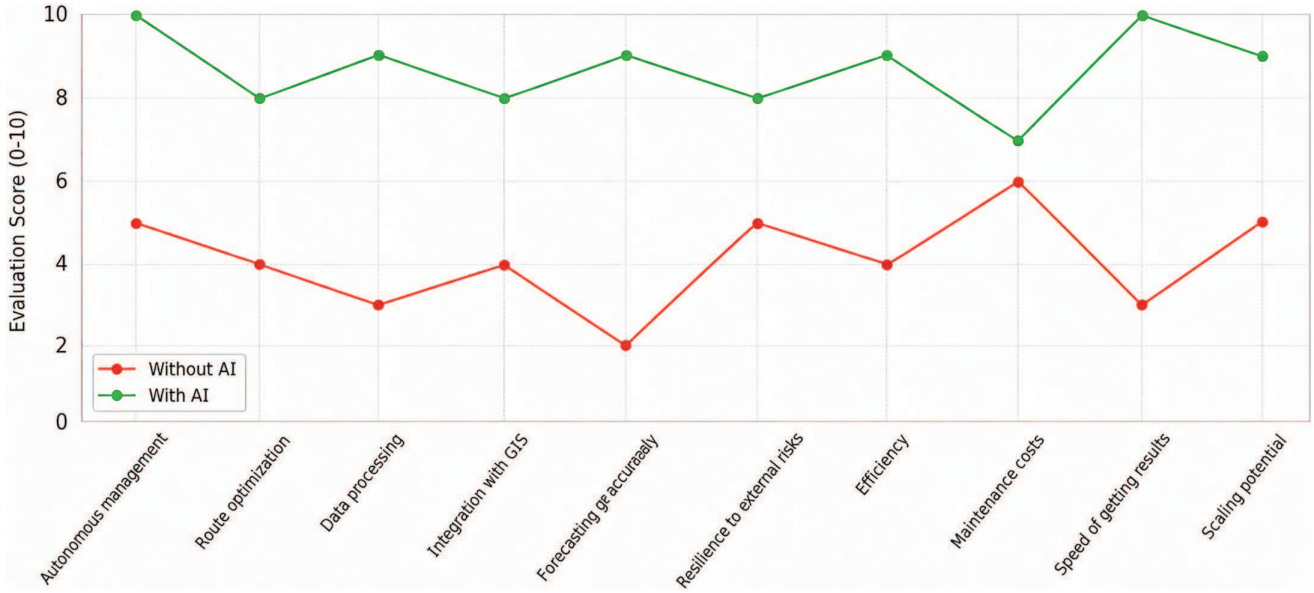
4.6.1. Challenges and strategies of AI-driven systems

Despite the benefits outlined above, there are key challenges to be considered with AI-enabled drone ports. First, data hungry: deep learning models need vast amounts of training data, which may be limited in remote geological areas of Kazakhstan. This issue can be partially resolved via transfer learning from geological data and semi-supervised learning techniques to minimize data labeling needs. Second, computational efficiency: the inference of AI requires a substantial amount of computational power, at the expense of the UAV's autonomy. Using lightweight models like

Table 8
Expert comparison of drone ports in the interests of geology without AI and with AI

Criteria's	Drone port without AI	Evaluation	Drone port with AI	Evaluation
Autonomous management	Operator required at all stages	5	Autonomous full cycle: launch, routing, analysis, completion	10
Route optimization	Preset routes ignore changing conditions	4	Real-time route adaptation based on weather and geological factors	9
Data processing	Manual or minimally automated processing	3	Neural AI modules enable automated data interpretation and classification	10
Integration with GIS	Partial, requires manual integration and post-processing	4	Auto-integration with ArcGIS/QGIS and spatial analytics	8
Forecasting geoanomaly	Absent	2	Trained DL models predict geostructures and anomalies	9
Resilience to external risks	Unstable in adverse conditions	5	Risk prediction, failure detection, adaptive routing, and safe flight windows	8
Efficiency	Operator-dependent and limited by mission duration	4	24/7 multi-drone operation with automated relaunch	9
Maintenance costs	Low adoption, growing scalability	6	High initial cost, but scalable and low maintenance	7
The speed of getting results	Results in a few hours or days	3	Near real-time processing and visualization with RTK and AI analytics	10
Scaling potential	Deployment and centralized management challenges	5	High scalability via network architecture and intelligent control	9

Figure 7
Line chart comparison of with and without AI expert scores



TinyML and MobileNet [29] is suggested to minimize onboard power while maintaining inference accuracy. Third, transparency: deep neural networks are black-box systems, which can lead to lower trust for the operator in critical safety decisions. Combining AI-human oversight models where AI results are presented as a recommendation requiring human confirmation can overcome this limitation. Fourth, transferability: pretrained models may not perform well in geological environments outside the training set. Adaptation methods and module-based retraining should be implemented. Finally, Kazakhstan's climatic conditions such as harsh winter temperatures in the northern steppe region (less than −40 C) and strong winds in the Tien Shan and Ustyurt plateau

affect the "autonomy" (K1) and "risk tolerance" (K6) criteria scores. This requires thermal insulation for port components on the drone, wind-speed-based mission abort protocols, and heated battery systems for sustained operation.

4.7. Expert prioritization of development directions

Table 8 presents eight expert-defined priority areas for UAV-based autonomous geomonitoring in Kazakhstan, evaluated by scientific relevance, national priority, and technological readiness (TRL 1–9).

Automation of AI-designed drone ports is key to the geomonitoring revolution in Kazakhstan. It is highly relevant, adaptable to remote areas, and of moderate maturity (TRL 6–7). Regulation is required for scaling autonomous solutions. The high significance is limited by low maturity (TRL 3–4) that prevents implementation of existing technologies. Geospatial cloud computing with AI analytics provides scalability. Although existing technologies (TRL 8–9) enable interoperable systems, local data silos limit their effectiveness. Figure 8 explains the comparison of different development directions based on their current technological readiness levels

UAV multisensory systems (LiDAR, hyperspectral, seismic) provide integrated geological monitoring. They enable multi-tasking missions and national deployment. Prescriptive AI modules transform geo-observation systems into predictive one. They are still in their infancy (TRL 4–5) but have high scientific and safety promise. Cybersecurity is growing in importance for network trust. Data security and confidentiality are particularly important for mining and infrastructure monitoring.

People development—training and simulation—provides long-term capacity. It does not stimulate innovation but enables the safe use of UAVs. Power efficiency and back-up power ensure uninterrupted operation in extreme environments. Current technologies need to be tailored to Kazakhstan's field conditions.

4.8. Recommendations from experts on AI-based autonomous drone ports

Improving the scientific-methodological foundation of effectiveness evaluation by developing and testing a universal multi-criteria model for AI-based geomonitoring systems that considers autonomy, performance, risk tolerance, cost, forecast accuracy, and scalability.

4.8.1. Technical recommendations for AI drone ports

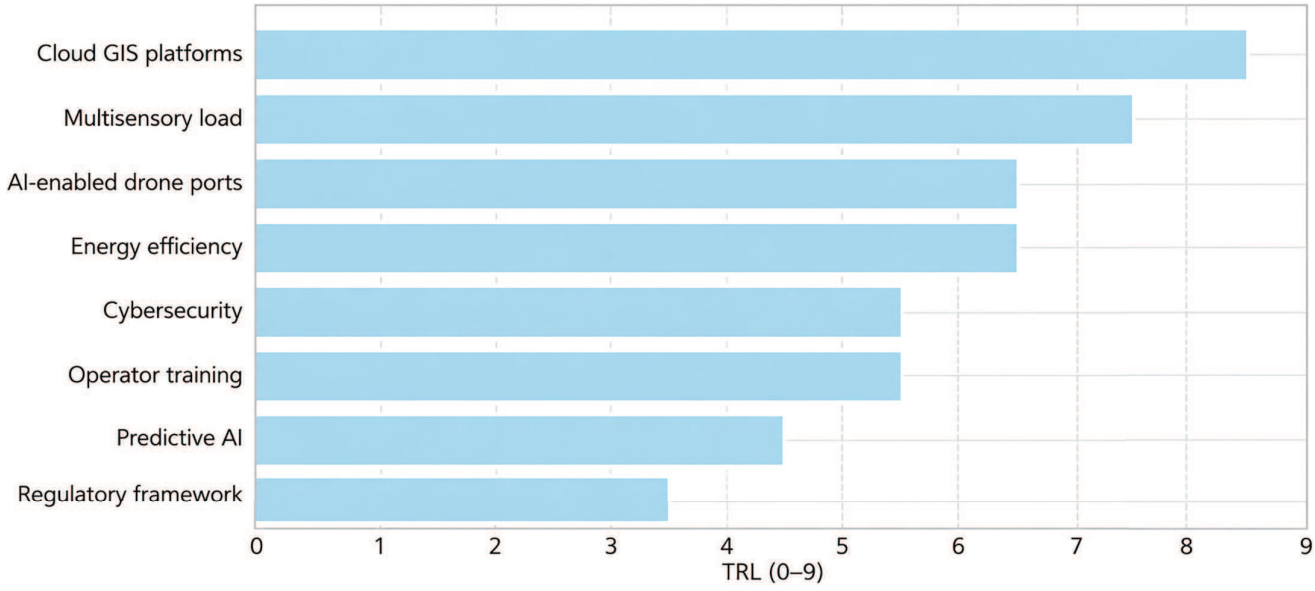
AI-based autonomous drone ports should integrate autonomy, adaptability, real-time data analysis, and scalability to improve geomonitoring efficiency. Intelligent mission planning, adaptive AI algorithms, and predictive analytics can support reliable operation and early hazard detection. A multi-criteria evaluation model should assess system performance, autonomy, risk, cost-effectiveness, forecasting accuracy, and scalability to validate practical applicability.

4.8.2. The technical, institutional and economic challenges of deployment

The implementation of an intelligent drone port in Kazakhstan will require meeting various requirements, such as aviation, airspace, data protection, and security. The registration of UAS with a maximum take-off weight of more than 0.25 kg and systems with data collection equipment is carried out. It also specifies that the registration certificate is not a license to operate. Registration and operational authorization should therefore be considered to be decision gates within the deployment plan.

The Law of the Republic of Kazakhstan on the Use of Airspace and Rules for the Use of Airspace should be used to determine the missions of a particular site. Additional coordination may be required where proposed routes to pass through restricted airspace, aerodrome zones, military areas, protected facilities, mines, energy installations, and/or critical infrastructure.

Figure 8
Comparison of different development directions based on their current technological readiness levels



The procedures for remotely supervised and automated operations should include also the following: Remote supervision, emergency intervention, geofencing, mission cancellation due to weather, communication failure, and safe flight termination.

Data governance is also an important factor of deployment. UAV imagery can include identifiable persons, vehicles, private property, and/or sensitive infrastructure. The information should be checked according to the Law of the Republic of Kazakhstan on Personal Data and Their Protection. The data-management architecture should include a plan for the proper collection, access, retention policies, encryption, audit trails, and secure deletion of data. If the information collected has been determined as personal information, then all the requirements for the consent to personal data collection, protection, and storage in a database within the Republic of Kazakhstan are applied.

Operational barriers are unreliable communication coverage, low power on the grid, battery degradation, high cold weather temperatures, high wind levels, calibration needs for the sensors, and the availability of spare parts and personnel trained in the operation of UAVs, GIS and geological interpretation. The selection of the site, mission availability, system architecture and life-cycle cost are relevant to these conditions. Therefore, regulatory authorisation, data administration, cyber security, communication backup and power backup and local maintenance capacity should be taken into account as a minimum requirement for any Kazakhstan pilot deployment.

4.8.3. Set up and pilot geomonitoring: areas in hazardous areas

Pilot studies in landslide-prone and geologically vulnerable regions of Kazakhstan, such as Zhetysu, the Tien Shan, and the Caspian region, can help evaluate the practical effectiveness of AI-based drone ports. By integrating multisensor UAVs with predictive analytics, the research can investigate geological anomaly detection, assess prediction accuracy, and validate early-warning performance under real-world conditions.

4.8.4. Strengthen multidisciplinary cooperation

Strengthening collaboration among universities, geological institutes, and technology companies can support joint research in AI, robotics, and geosciences, helping develop and validate reliable, scalable AI-based geomonitoring systems.

4.8.5. Enhance the sustainability and safety

The sustainability and safety of AI-based drone ports should be investigated through robust cybersecurity, reliable backup communication, and energy-efficient power management. Solar and hybrid energy systems may improve operational continuity in remote areas, while secure telemetry storage can help protect data integrity. Future research should evaluate these solutions under field conditions, focusing on system reliability, energy efficiency, and resilience to environmental challenges.

4.8.6. Cost-benefit framework for deployment

The economic evaluation of intelligent drone-port deployment needs to be differentiating between CapEx, annual OpEx, and scheduled replacement costs and measurable benefits. Items which are subject to capital expenditure, include: UAVs, intelligent drone ports, sensor payloads, communication equipment, servers, site preparation, installation & system integration. These include personnel costs, energy costs, software licences, cloud or local data storage, communication costs, insurance premiums, regulatory compliance, calibration, preventive maintenance, repairs and field visits. Replacement expenditure refers to batteries, UAV components, sensors and computing equipment.

Potential measurable gains are: fewer manual visits to fields, travel time and fewer people exposed to hazardous areas, and fewer delays in data processing. Avoidable loss benefits should only be added when there is historical loss data that substantiate the loss and an explicit attribution approach.

When the length of deployment is T years the NPV should be calculated as follows:

$$NPV = -C_0 + \sum_{t=1}^{T} \left(\frac{B_t - C_t}{(1+r)^t} \right) \tag{5}$$

where C_0 is the amount of money that they start with, and

B_t is the actual amount of the benefit at year t, and C_t. The operating and replacement cost in year t is denoted by is and the discount rate is denoted by r. The economic evaluation should present the net present value, benefit–cost ratio, annualized operating cost per port and discounted payback period, per pilot deployment, regional deployment, and national scale deployment scenarios.

In the current study, no effort was made to gather auditable vendor quotations, operating cost records, and documented benefit information. Hence, the payback periods mentioned above (4–6 years and 7–10 years) have been deleted. The payback period should only be determined in a numerical format after a pilot implementation of the project where required financial inputs are collected. Table 9 explains the component required to implement the economic assessment focusing on different parameter such as capital expenditure, software and integration, annual operations, maintenance, and replacements.

4.8.7. Create training programs

For new-generation drone port operators in AI mission control, multisensory data analysis, and GIS in Table 10. Develop virtual simulators for training. Create deep learning-based AI modules for geoanomaly prediction based on temporal and spatial data. Comply with integration with UAV onboard systems and post-processing software (QGIS, ArcGIS, and Google Earth Engine).

This research supports the growing importance and technological readiness of smart autonomous drones for long-term geological monitoring in Kazakhstan. AI-driven drone ports signify transition from "toy" UAV applications to data-driven platforms. Multisensory platforms, AI modules, and cloud GIS allow for more precise data acquisition and quicker, more reliable geoanomaly prediction.

Multi-criteria analysis by experts confirms the benefits of AI systems in autonomy, accuracy, scalability, and responsiveness. These insights underpin the shift from reactive to proactive geo-risk prevention, especially in remote and vulnerable regions. Critical areas of development—regulatory compliance, cloud technologies, and predictive analytics—are critical for practical deployment. Although simulations are effective for model evaluation, some differences between the virtual and real world need to be taken into account. During deployments, sensor inaccuracies, environmental conditions (e.g., wind, temperature variations), and potential delays in telemetry in remote areas may influence system behavior. The suggested approach includes adaptive

Table 9
Priority areas for autonomous geomonitoring system development

The direction of development	Scientific and technical significance	Relevance for Kazakhstan	Technological feasibility (TRL)	Priority
AI-enabled automated drone ports	High—mission cycle autonomy	High—hard-to-reach objects	6–7 (demo and pilot zones)	Very high
Cloud GIS integration and analytical platforms	High—multiscale data	Medium—regional initiatives	8–9 (industry-specific solutions are available)	High
Regulatory framework for UAV-based monitoring	Medium—legal, managerial	High—a gap in regulation	3–4 (under development)	Very high
Cybersecurity of UAV infrastructure	High—data and communication protection	Medium—relevant for critical zones	5–6 (developing area)	High
Multisensory load (LiDAR, spectra, seismic)	High—key to multitasking	High—the variety of objects	7–8 (there are mature solutions)	High
Operator training and digital simulators	Medium—staff stability	Medium—lack of specialists	5–6 (development started)	Medium
Predictive AI for geo trend analytics	Very high—science and safety	Medium—we need to switch to predictions	4–5 (research stage)	High
Energy efficiency and backup power systems	Medium—system stability	Medium—especially in the mountains/steppes	6–7 (commercial prototypes)	Medium

Table 10
Components required for the economic assessment

Cost category	Components
Capital expenditure	UAVs, IDPs, sensors, communication equipment, servers, installation, and site preparation
Software and integration	GIS licences, AI development, cloud services, cybersecurity, and integration
Annual operation	Personnel, energy, connectivity, insurance, permits, storage, and field support
Maintenance	Calibration, preventive maintenance, repairs, batteries and spare parts
Replacement	UAV, battery, sensor, and computing replacement schedules
Benefits	Reduced field missions, labour savings, faster reporting, and documented avoided losses

planning, sensor fusion, and resilient communication strategies to address these issues. This approach increases system robustness and reliability in field conditions.

The climatic conditions in Kazakhstan, i.e., the cold weather and fast winds, play a significant role in the operations of UAV. These factors impact the battery life, the reliability, and autonomy of the system. In order to address these challenges, the proposed system will involve the adaptive mission planning, thermal insulation, and wind-aware policies, which will ensure the stability of operation under variable weather conditions.

Geomonitoring involves an information ecosystem that encompasses UAVs, smart drone ports, cloud GIS, and AI applications to support real-time data acquisition, processing, and decision-making in the cloud.

An extensive cost–benefit assessment shows that AI-based drone-port systems have higher upfront costs, resulting from infrastructure, hardware and software installation. But this cost is compensated by substantial long-term savings in operational costs in terms of labor costs, automation of monitoring process, and cost of field survey. Moreover, the timely identification of geological risks (such as landslides and subsidence) helps avoid potential infrastructure damage and subsequent emergency management costs. In terms of economic outcomes, pilot-scale deployment (3–5 drone ports) is likely to attain payback period within 4–6 years, whereas a large-scale national deployment can reach payback period within 7–10 years because of economies of scale and system efficiencies. The results demonstrate the cost–effectiveness and strategic importance of smart geomonitoring systems for decision-making.

5. Conclusion

This research offers a holistic evaluation of the opportunity for incorporating smart drone ports into Kazakhstan's geomonitoring networks. Using a multidimensional analysis framework that involves architectural modeling, assessment of AI system, and expert opinion, the study confirms the scientific and practical feasibility of using autonomous, AI-powered technologies for large-scale geomonitoring. The findings also highlight the interdisciplinary and socioeconomic values. Autonomous geomonitoring networks can improve environmental safety, facilitate emergency response, and enable more sustainable land-use

management, generating long-term value for government agencies, industry and science. The proposed framework will support the future deployment of predictive models, standardization of approaches and scalable infrastructure. It also provides opportunities for interdisciplinary interaction between engineers, geologists, data scientists, and policymakers. The deployment of an adaptive, robust, and smart monitoring network is a key step in enabling proactive geological risk management for growing anthropogenic and climate-related threats. Future research should focus on enhancing AI-driven anomaly detection, ensuring maximum drone autonomy in variable conditions, as well as the data fusion method by integrating with satellite and on-ground sensors. Also, future sustainability will require more international collaboration and establishment of regulations of autonomous monitoring technologies.

In terms of practical implementation, the suggested approach should be the creation of pilot port zones of drones in 2–3 critical regions (Zailiysky Alatau, Shubarkol coal basin, Caspian coastal zone) at TRL 6–7, finalization of the regulatory framework of autonomous UAVs operation in two years (with the Civil Aviation Committee of Kazakhstan), and scaling to a national network after successful piloting and confirmation of Return on Investment (ROI). The number of scenarios in this study, which are based on a long-term observation of field conditions, is very small. The findings highlight the feasibility and benefits of implementing AI-powered drone ports for geomonitoring, but further studies are needed to involve pilot versions and validate the system with actual geological monitoring data captured by UAVs in the long term in a representative area in Kazakhstan. The next step in development should be the piloting of the proposed approach and its integration into the national geomonitoring system and development of adaptive AI models to operate in the conditions of a changing environment. This will also facilitate the reliability, scalability, and implementation of smart geomonitoring systems.

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Ethical Statement

This study involved survey-based data collection and expert interviews conducted for academic research purposes. In accordance with the guidelines of LLP «Research and Development Center «Kazakhstan Engineering», formal ethical approval was not required for this type of non-sensitive, non-interventional research. An official statement confirming the exemption has been issued by the institution (Document No. 04-1-9/231). All participants provided informed consent, participated voluntarily, and remained anonymous throughout the study.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Gani Baiseitov: Conceptualization, Methodology, Validation, Writing – original draft, Supervision, Project administration, Funding acquisition. **Alexey Semchenko:** Formal analysis, Resources, Writing – original draft. **Daulet Toibazarov:** Software, Investigation, Resources, Data curation. **Praveen Kumar:** Software, Validation, Writing – original draft, Visualization. **Zarina Kutpanova:** Formal analysis, Writing – review & editing.

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