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Evaluation of Flood Protection Infrastructure Safety through Satellite Image Analysis with Artificial Intelligence Methods*

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Abstract

The increasing frequency of extreme weather events caused by climate change highlights the urgent need for reliable tools to support flood risk management. Traditional inspection methods for levees, polders, and related hydraulic structures are limited in terms of coverage, cost, and timeliness. In this paper, we propose an original information system that integrates high-resolution satellite imagery with artificial intelligence to enhance the monitoring and safety assessment of flood protection infrastructure. The system architecture combines data from Planet Labs (Dove and SkySat) and Copernicus Sentinel missions with meteorological and IoT sources. Data are automatically acquired and preprocessed before being analyzed using advanced machine learning models, including convolutional neural networks (U-Net, DeepLabV3), recurrent networks (LSTM) for time series, and ensemble classifiers (XGBoost, Random Forest). The models focus on detecting anomalies such as excessive vegetation growth, soil moisture changes, seepage, erosion, and potential structural deformations. Results are integrated into a decision-support module that incorporates expert rules, fuzzy logic, and probabilistic reasoning to generate alerts and risk maps. A presentation layer provides GIS-based visualizations and interactive dashboards for end-users, while the modular microservices architecture ensures scalability and interoperability. The main contribution of this research is the design of a multilayered, AI-driven framework that demonstrates how Earth Observation data can be transformed into actionable knowledge for infrastructure safety management. Although the system is currently at a conceptual or pilot stage, preliminary testing indicates its potential for supporting public authorities, crisis management services, and local communities in flood-prone areas. Future work will address large-scale validation, integration with hydrological and meteorological forecasting, and extension to broader environmental applications such as wetland monitoring and land cover change detection.

Keywords: Artificial Intelligence, Satellite Imagery, Flood Protection Infrastructure, Risk Management, GIS, Earth Observation.

Introduction

The security of flood protection infrastructure, including levees and polders, plays a crucial role in safeguarding the population, property, and the natural environment in flood-prone areas. Effective maintenance of these structures requires systematic monitoring of their technical condition and the early detection of any anomalies that may reduce their effectiveness. One of the significant factors influencing the condition of flood protection infrastructure is vegetation growth—both natural and invasive—which can affect the stability of levees and the capacity of retention areas. Excessive or uncontrolled vegetation on the crests and slopes of levees may lead to the degradation of their structure by weakening soil cohesion, increasing water infiltration, and hindering the

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performance of technical inspections. Conversely, inadequately managed vegetation in polders can reduce their retention capacity and limit the efficiency of water outflow. For this reason, the development of tools that enable rapid and precise detection of land cover changes, including the degree of vegetation overgrowth, becomes essential.

This article presents a research approach based on the use of satellite imagery combined with artificial intelligence methods and modern information systems to assess the maintenance condition of flood protection infrastructure. The application of image processing techniques and machine learning enables the automation of land cover classification, the identification of undesirable vegetation changes, and supports management decisions related to the maintenance and modernization of hydraulic engineering structures. This approach is part of the broader context of developing environmental monitoring systems and intelligent management of critical infrastructure.

Literature Review on the Application of Satellite Monitoring and Artificial Intelligence Systems in the Field of Flood Safety.

The conducted literature review demonstrates the growing role of artificial intelligence and satellite monitoring in assessing the condition of flood protection infrastructure. Particularly important is tracking vegetation growth, which may affect the state of levees—both in terms of detecting erosion and changes in retention capacity. Technologies involving visual monitoring of infrastructure, combined with radar technologies (Synthetic Aperture Radar), as well as data collected directly by supervising personnel and integrated with artificial intelligence, have proven effective in detecting situations that threaten the proper functioning of flood protection infrastructure. In this field, satellite systems are being increasingly employed.

In study (Lee and Li, 2025), Lee and Li present a comprehensive review of GeoAI applications for flood extent mapping using SAR and multispectral satellites. They discuss available datasets, such as Sen1Floods11, DigiFlood, and FloodNet, along with commonly used CNN and Vision Transformer (ViT) architectures. Techniques to reduce cloud interference (e.g., cloud augmentation) and hybrid approaches combining AI with hydrodynamic models are highlighted. The authors also emphasize the potential of onboard satellite processing. They stress the need for standardized data formats, adaptation to local conditions, and long-term system resilience. Future directions include multisensor integration and vegetation change analysis in floodplains.

Study (Meng, Xu and Zhu, 2025) presents research comparing the performance of ViT, DeepLabV3, U-Net, and Random Forest models on the Sen1Floods11 dataset for the Rio Colima region. ViT achieved an accuracy of 94% and IoU of 88.7%, outperforming other models. Techniques for augmenting multispectral and SAR data were demonstrated, with particular emphasis on integrating multiple wave frequencies and enhancing floodplain detection. The analysis also examined the impact of training parameters such as epoch number and batch size. Based on the results, the authors recommend ensembles and automated algorithms for tagging ground-truth data, justified by the need for flexibility with respect to local conditions.

Study (Shafiei et al., 2024) introduces a deep learning framework for rapid flood mapping using multispectral imagery (Sentinel-2). The authors employed U-Net and DeepLabV3+ and implemented cloud masking and gap-filling. Validation was conducted across seven Asian regions, achieving accuracy above 92% and AUC ~0.95. The system generates flood maps with a low false alarm rate, directly supporting emergency response services. Real-time implementation was also considered, offering a practical decision-support tool for crisis management.

Study (Gupta and Khan, 2024) reviews AI methods used in flood risk management, incorporating hydrological, satellite, and meteorological data. The authors discuss AI for flood forecasting, extent estimation, and intensity assessment. Hybrid predictive models combining statistical methods with deep learning are presented. Challenges such as lack of historical data, explainability, and model adaptation to diverse climatic regions are addressed. The importance of community integration and crowdsourcing for improving risk models is also emphasized.

Smidth et al. report research on AI and remote sensing tools for levee defect detection in the United States. High-resolution satellite imagery (WorldView-3) and SAR images were analyzed. AI identified cracks, erosion, excessive vegetation growth above thresholds, and structural weaknesses. Results showed a 35% reduction in overlooked defects and a 60% reduction in inspection time. The authors propose integrating satellites, drones, and field inspections into national infrastructure monitoring programs (Smith et al., 2025).

Report (Farmonaut, 2025) describes the Farmonaut Engine platform for levee monitoring using Sentinel-2, Landsat 8, and UAS drones. Multispectral and RGB analysis with AI enabled land cover classification and anomaly detection such as landslides, vegetation overgrowth, and leakages. Tests conducted in Poland, Germany, and France demonstrated effectiveness in identifying vegetation above 10 cm and in providing rapid reporting. The system supports maintenance planning and reduces response times of technical services.

Study (Kołodziejczyk and Zieliński, 2025) reviews applications of high-resolution satellite imagery for analyzing flood damage in mountainous regions, focusing on vegetation changes, landform morphology, and landslides. Sentinel-1/Sentinel-2 and PlanetScope data were used, covering both monsoon periods and episodes of intense rainfall. Results indicate that vegetation growth on slopes and levees is a clear sign of destabilization and should trigger detailed infrastructure inspections.

Study (Torres and Martínez, 2023) focuses on global flood mapping using optical remote sensing. The authors discuss vegetation indices (NDVI, NDWI, SAVI) and radiometric techniques for assessing vegetation cover and soil moisture. Sentinel-2, Landsat 8, and PlanetScope datasets were employed in a multi-year analysis of riverine areas. Findings reveal that vegetation growth on levees reduces their effectiveness and may indicate early erosion stages. The study concludes with recommendations for regular monitoring and establishing threshold values for vegetation indices.

In study (Huang and Silva, 2024), the authors present the integration of satellite data with “social sensing” (posts, images from residents) for rapid flood detection. Optical and SAR images were complemented with local community input. Results showed a 30% improvement in detection time compared to satellite data alone, and better coverage of remote areas. For instance, reports of vegetation growth on levees from residents enabled earlier detection of potential weaknesses than remote sensing tools.

Study (Ivanov et al., 2025) reviews deep learning applications in natural disaster management, including floods, hurricanes, and wildfires. CNNs, RNNs, GANs, and transfer learning techniques are discussed. Special attention is given to vegetation indices as indicators of environmental change. The authors emphasize the importance of monitoring vegetation growth along flood levees as an early warning sign of weaknesses. They recommend combining remote sensing data with physical models and Earth Observation Systems.

A broad review of AI in Earth Observation (Tuia et al., 2023) examines CV and ML models, integration of physical knowledge, and explainable AI. Applications in vegetation monitoring and deforestation are discussed, with potential adaptation to levee assessment. The need for standardization and data system interoperability is stressed. Trends include hybrid networks, transfer learning, and federated privacy-preserving solutions.

Study (Jiang et al., 2023) presents a method for generating annual vegetation height maps (10 m resolution) in alpine regions using Sentinel-2 and deep networks. Validation was performed against LIDAR data and in-situ measurements. Results with RMSE ~1.2 m allowed detection of vegetation growth at varying scales. The authors argue that this approach can be applied to flood levees, where significant vegetation height indicates lack of maintenance. They propose quarterly monitoring and incorporating vegetation height indices into infrastructure safety assessments.

In light of growing climate risks and the ongoing aging of hydraulic infrastructure, the use of modern technologies—particularly artificial intelligence and satellite imagery—becomes not only justified but essential. The application of machine learning algorithms to remote sensing data enables automatic and regular monitoring of levees, polders, and surrounding vegetation. Such approaches allow for early threat detection, reduced response times of technical services, and optimized maintenance efforts. These methods align with global trends in the digital transformation of flood risk management and intelligent supervision of critical infrastructure, as confirmed by numerous recent studies. Consequently, the development and implementation of such solutions represent a research direction with high scientific, practical, and societal potential.

Satellite Data Acquisition Capabilities for Monitoring Flood Protection Infrastructure.

A contemporary approach to flood protection infrastructure monitoring increasingly relies on satellite data as a primary source of spatial information. In the face of growing climate risks, frequent extreme events, and aging hydraulic infrastructure, it is essential to implement solutions that enable ongoing and objective monitoring of levees, polders, and other flood protection structures. Of particular importance is the use of data from Sentinel-1 and Sentinel-2 satellites, which provide access to high-quality radar and optical data of varying resolution, spectral properties, and update frequency. Data from the Sentinel-1 mission, implemented by the European Space Agency within the Copernicus program, consist of Synthetic Aperture Radar (SAR) imagery collected in the C-band. A major advantage of this dataset is its independence from weather conditions and the ability to acquire information both day and night. This enables continuous surveillance of the technical condition of levees, especially during periods of heavy rainfall and flooding. Radar interferometry (InSAR), based on analyzing phase differences between successive images, allows the detection of vertical ground displacements as small as a few millimeters. This makes it possible to identify potential deformations, subsidence, or other structural anomalies before they become noticeable in the field (Bamler and Hartl, 1998).

Thanks to their strong penetration capability through vegetation layers and sensitivity to moisture changes, SAR data can also be used to identify areas where abnormal vegetation growth occurs within levee zones. Biomass accumulation on levee crests may indicate a lack of regular maintenance and the risk of structural threats. Combined with analyses of phenomena such as seepage, waterlogging, and uneven settlement of levees, it is possible to build a comprehensive picture of the hydrotechnical situation of a given area. Sentinel-1 imagery can also be processed using texture classification algorithms (e.g., GLCM), enabling the detection of microscopic changes in levee surface structure, which supports maintenance planning.

Complementing radar data are optical images from Sentinel-2 satellites. With 13 spectral bands and spatial resolution down to 10 meters, Sentinel-2 imagery allows precise monitoring of land cover and vegetation dynamics, which may indicate irregularities in infrastructure functioning. Particularly useful are indices such as NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index), which are used to assess vegetation condition and soil moisture levels. Excessive or invasive vegetation growth on levee crests can weaken their stability, making systematic monitoring of these indices essential for ensuring structural integrity (Gorelick et al., 2017)(Huang and Silva, 2024).

Sentinel-2 imagery is available in pre-processed form (Level-2A), meaning it has undergone initial atmospheric correction. Bands B8A, B11, and B12 are especially useful in soil moisture monitoring and vegetation assessment, as they correspond to the near- and shortwave-infrared spectrum, which is highly sensitive to water content and plant structure. In many cases, indices such as SAVI (Soil-Adjusted Vegetation Index) or EVI (Enhanced Vegetation Index) provide more precise results than classical NDVI, particularly in areas with a high proportion of bare surfaces.

It is worth noting that both Sentinel-1 and Sentinel-2 data are open-access and free of charge, enabling their use in a wide range of applications—from research projects to operational decision-support systems. An example is the Google Earth Engine platform, which facilitates the processing and analysis of large satellite datasets in near real time. This tool allows for complex land cover change analyses and automated generation of flood hazard maps. The literature highlights the growing importance of integrating satellite data with artificial intelligence algorithms, which enables automation of classification processes and faster detection of irregularities in hydraulic structures (Raspini, Bianchini and Moretti, 2018)(Shafiei et al., 2024).

Satellite data can also be combined with observations collected by unmanned aerial vehicles (UAVs), enhancing the accuracy and spatial resolution of field analyses. For hard-to-reach hydraulic structures, drones equipped with optical or hyperspectral sensors provide supplementary data with resolutions of several centimeters per pixel. By combining UAV and satellite imagery, it is possible to create spatial models and orthophotos that form the basis for detailed inventories of flood protection structures. This approach has been applied in projects conducted in Germany, the Netherlands, and Poland, where Sentinel data served as a foundation for the automated detection of erosion and seepage zones.

Beyond Sentinel missions, U.S. Landsat 8 and 9 satellites also play an important role, offering multispectral imagery across a broader spectral range, albeit with lower update frequency. In practice, combining data from multiple sources allows the creation of hybrid models that increase the accuracy and reliability of analyses. Commercial platforms such as PlanetScope and Maxar are also increasingly used, providing sub-meter resolution imagery. Although access to these datasets involves costs, in many cases—especially in the context of strategically important infrastructure—their use is fully justified (Smith et al., 2025).

Additionally, satellite data can be employed for long-term land cover change trend analyses, which help assess the effectiveness of maintenance and investment activities. For example, comparing time series of NDVI and NDWI makes it possible to identify areas of changing vegetation density or uncontrolled inundation. Such analyses also support decision-making processes related to levee revitalization, modernization of water culverts, or construction of new retention basins.

An important aspect of satellite data acquisition is preprocessing, which includes atmospheric correction, cloud removal, radiometric and geometric calibration, and temporal alignment. For optical data, the presence of clouds is a particular challenge, as it can significantly reduce image quality. Specialized algorithms such as Sen2Cor and Fmask are used to identify and mask cloud-covered areas and interpolate missing data. For radar data, interferometric calibration is crucial, as it directly affects the accuracy of deformation analyses (Wegmüller et al., 2010).

Data fusion methods are also gaining popularity, combining different types of information (SAR, optical, LiDAR, social data) to provide a more comprehensive picture. Examples include monitoring systems that incorporate social sensing, such as geotagged photos or citizen reports, which complement satellite data with locally specific information not easily captured from orbit. In the future, the development of integrated real-time monitoring platforms is anticipated, combining satellite data with UAVs, ground sensors, and crowdsourced inputs (Xie, Sha and Yu, 2020).

Modern capabilities for satellite data acquisition in the context of flood protection infrastructure monitoring are broad and rapidly evolving. Their availability, diversity, and integration with advanced data analysis methods, including artificial intelligence algorithms, form the foundation of next-generation flood risk management systems. Investments in the development of such solutions are fully justified both from an engineering and public policy perspective. The application of satellite data increases public safety, enhances the effectiveness of preventive measures, and reduces the costs associated with flood damage mitigation.

Programming Libraries, Services, and Tools Enabling Access to atellite Data for Flood Protection Infrastructure Monitoring.

Modern flood risk management systems increasingly rely on the analysis of remote sensing data acquired from diverse satellite observation platforms. To effectively harness the potential of these data, it is essential to use advanced IT tools that enable searching, processing, and analysis. These tools include both programming libraries used in Python and R, as well as dedicated web services and analytical platforms that support institutions responsible for the maintenance of flood protection infrastructure. One of the most important and versatile tools for working with satellite data is Google Earth Engine (GEE). This cloud-based platform provides access to petabytes of data from Sentinel, Landsat, MODIS, and many other missions. Google Earth Engine enables programmatic queries and data analyses using JavaScript or Python, and also supports the creation of complex web applications for land cover analysis, moisture change detection, and vegetation condition assessment on flood levees. A key advantage of GEE is the ability to perform scalable time-series analyses, such as detecting NDVI anomalies in levee zones or identifying areas of flooding. Another noteworthy tool is the Sentinel Hub platform, which provides browsing and download capabilities for Sentinel-1, Sentinel-2, Landsat, and MODIS data. Sentinel Hub offers the EO Browser, an interactive tool for analyzing optical and radar data and for generating custom scripts in Evalscript to visualize indicators such as NDVI, NDWI, or the Moisture Index. This platform can be used for rapid identification of areas with high erosion risk or excessive vegetation growth on levees, which may indicate a lack of maintenance. In the context of more advanced spatial analyses, programming libraries in Python play a critical role, such as:

- Rasterio – for reading and writing raster data (GeoTIFF, NetCDF),
- GDAL/OGR – the foundation for geographic data operations,
- xarray and rioxarray – for handling multidimensional satellite datasets,
- Sentinelsat – a library for searching and downloading data from the Copernicus Open Access Hub (formerly SciHub),
- Pyproj – for spatial coordinate transformations,
- scikit-image, OpenCV, scikit-learn, TensorFlow – for image analysis, classification, and machine learning algorithm implementation.

For users preferring point-and-click tools, a valuable data source is the Copernicus Data Space Ecosystem – the official European Space Agency service providing access to Sentinel-1, -2, -3, and -5P data, with functionality for building spatial and temporal queries. Alternatively, the U.S. Geological Survey's Earth Explorer platform enables downloading of Landsat, ASTER, and MODIS datasets, complementing European observations with long-term historical records.

Also noteworthy is Planet.com, a commercial platform offering access to very high-resolution satellite data (up to 50 cm/pixel) with high revisit frequency (several times per day). Planet provides data from its Dove and SkySat constellations, which can be particularly valuable for precision monitoring of levees, especially in flood situations where rapid detection of damage and seepage is critical. Planet offers APIs for integrating data with GIS systems, as well as web tools for browsing and ordering archival and current imagery. Through cooperation with public and research institutions (e.g., under the NICFI program supporting deforestation monitoring), free access to selected datasets is also available.

In practice, monitoring activities for hydraulic infrastructure require not only access to imagery but also its integration with meteorological, hydrological, and topographic data. For this purpose, aggregating services are often used, such as Open Data Cube, TerrSet, QGIS with the Semi-Automatic Classification Plugin, or ILWIS tools developed by ITC at the University of Twente. QGIS offers the ability to automate NDVI time-series analyses, import data from Sentinel Hub, integrate with Python, and visualize spatial data at the local level. Some platforms also allow for terrain deformation monitoring using InSAR techniques. An example is the GEP (Geohazards Exploitation Platform), created by ESA, which provides processed deformation products based on Sentinel-1 data. Such data are crucial for assessing the stability of the ground beneath levees, and their analysis enables the prediction of potential failures and local subsidence.

In recent years, services based on artificial intelligence and automated change detection have also gained importance. An example is the Descartes Labs platform, which enables real-time classification of satellite imagery and the development of predictive models using satellite and meteorological data. Similarly, platforms such as Satelligence and UP42 offer analytical tools for detecting hydrological hazards, object detection, and monitoring land-use changes using deep learning methods.

An Original Information System for Supporting the Assessment of Flood Protection Infrastructure Risks.

In the face of growing climate risks and the increasing frequency of extreme events such as heavy rainfall and floods, it has become necessary to implement advanced systems for monitoring hydraulic infrastructure. This applies in particular to flood levees, polders, and other elements that protect residential and agricultural areas. Traditional inspection methods, based on visual surveys, are time-consuming, costly, and do not provide sufficient inspection frequency. Therefore, satellite data are playing an increasingly important role in this field, enabling remote, repeatable, and objective monitoring of large areas. The proposed system aims to create a comprehensive IT solution to support the assessment of the technical condition of flood protection infrastructure, based on satellite imagery and artificial intelligence methods. A key element of this architecture is integration with the data access system provided by Planet Labs, selected as the primary source of imagery due to its exceptional spatial resolution and acquisition frequency. Dove and SkySat satellites provide data with a resolution of 0.5–3 meters and can capture images of a given area several times a day. Such quality and frequency of imagery allow for the rapid detection of changes on levee surfaces, such as cracks, seepage, erosion, or uncontrolled vegetation growth.

The system architecture has been designed in a modular way and consists of five main functional layers. The first is the data acquisition layer, which is responsible for automatically downloading imagery from the Planet Labs service via the available API. The system allows defining Areas of Interest (AOIs), scheduling queries, and filtering images by quality (e.g., cloud cover level). Additionally, data may be supplemented with imagery from Sentinel-1 (SAR) and Sentinel-2 (optical), which are low-cost and publicly available. Meteorological data (precipitation, air humidity) from services such as OpenWeatherMap or from local IoT sensors can also be integrated. The next component is the preprocessing layer, which prepares data for further analysis. Data are transformed into consistent coordinate systems and spatially clipped according to the analyzed areas (e.g., individual levee sections).

The analytical layer forms the core of the system, relying on artificial intelligence and machine learning methods. Convolutional neural networks (CNNs), such as U-Net or DeepLabV3 architectures, are used for analyzing image data, enabling segmentation of risk areas and anomaly detection (e.g., seepage points, deformations, surface texture changes). In addition, recurrent neural networks (e.g., LSTMs) are applied to analyze time series of vegetation and moisture indices, enabling detection of long-term changes. Classification models such as XGBoost and Random Forest are used to assign risk levels to specific sections of infrastructure based on a set of input features (e.g., NDVI, NDWI, slope, intensity of land cover changes). The model can be locally trained using reference data from field inspections or historical reports.

The decision-making layer performs an expert function, generating alerts and interpreting AI model results. It includes expert rules (e.g., "NDVI > 0.7 for 3 weeks on a levee crest → high risk level"), a fuzzy system for evaluating combinations of factors (e.g., moisture + cover + deformation), and a logical inference engine. Alerts are generated automatically and may be sent to end users (engineers, infrastructure managers, emergency services) via e-mail, SMS, or system notifications. Periodic reports can also be generated in PDF or GeoPDF formats, and spatial data can be exported as WMS or GeoJSON layers to GIS systems.

The final layer is the presentation layer, which provides users with access to a web interface and GIS tools. The interface is built on modern visualization technologies and allows interactive analysis of spatial data—for example, clicking on a levee section displays its NDVI change history, local alerts, and predicted trends. The system also allows the generation of hazard maps that can be published as dynamic map layers. For advanced users, an administrative panel is available to configure detection parameters, alert thresholds, and field inspection schedules.

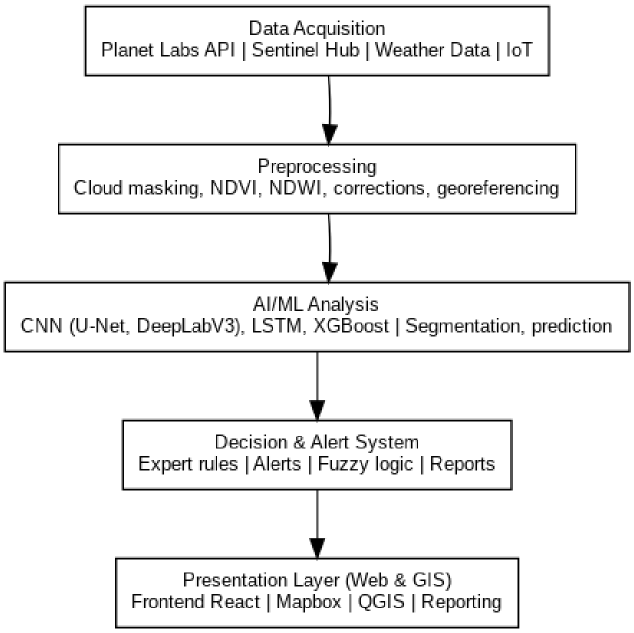

Fig. 1. Data Processing Sequences

The entire architecture is based on a microservices approach, in which each component operates as an independent unit deployed in a container (Docker). Services communicate via REST APIs, and data are processed both in batch and streaming modes using Apache Kafka and Airflow. Image data are stored in a file repository (e.g., Amazon S3 or Azure Blob), while metadata, alerts, and user configurations are stored in a relational PostgreSQL database with PostGIS spatial extensions.

The system can be deployed in public or private cloud environments, or as a local installation within a crisis management structure. An additional value of the system is its integration with mobile devices (e.g., an application for field inspectors), which enable local confirmation or verification of automatically detected alerts. Augmented Reality (AR) components may also be implemented for on-site data visualization. Thanks to its modular structure, the system can be gradually expanded with additional data sources (e.g., UAV or LiDAR) and new analytical functionalities. In summary, the architecture of the AI system combines the advantages of high-resolution satellite data provided by Planet Labs with modern methods of data analysis and machine learning.

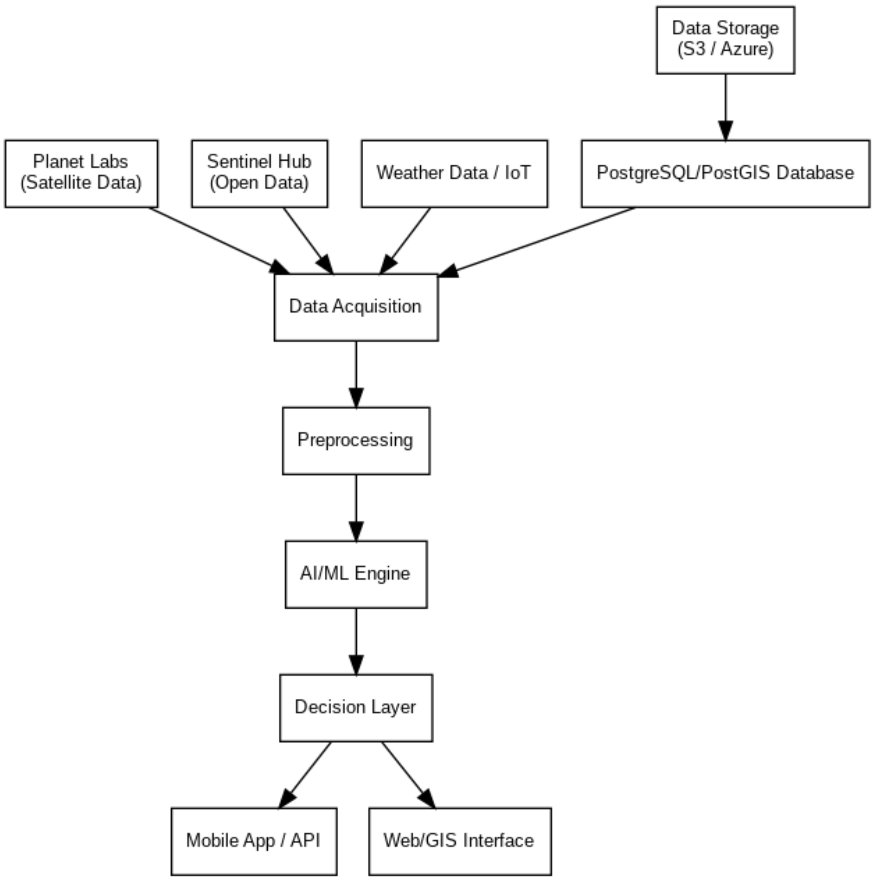

Fig. 2. Modular System Architecture

This type of solution aligns with current trends in the digitalization of critical infrastructure management and the use of Earth Observation in risk management. The system can significantly contribute to improving the effectiveness of levee monitoring, accelerating threat response, and optimizing maintenance activities. The data processing sequences in the proprietary software are presented in Figure 1, while its division into functional modules is shown in Figure 1.

Summary

The approach proposed in the article to support the monitoring of flood protection infrastructure safety using satellite imagery and artificial intelligence methods confirms the rationale for integrating modern data sources with machine learning algorithms. The system presented in this study, thanks to its multilayered architecture encompassing data acquisition, processing, and analysis modules, along with decision-making and presentation layers, represents a potential tool for supporting entities responsible for the maintenance of hydraulic infrastructure, such as flood levees and polders.

Despite positive test results and a high level of process automation, it should be noted that the system is currently at a conceptual or pilot stage. Therefore, further research is required, including long-term deployment and observation under real-world conditions. It will be particularly important to evaluate the system's effectiveness under different seasonal conditions, with varying vegetation dynamics and hydrological variability. Additionally, an analysis of the long-term stability of machine learning algorithms is necessary, especially regarding their adaptability to changing input data.

Further system expansion also appears justified, including the integration of additional data sources—such as high-resolution radar data (e.g., TerraSAR-X satellites), ground-based hydrometric sensors, or real-time meteorological data. Integration with meteorological or hydrological forecasting systems could further improve the accuracy and precision of generated alerts. Extending the decision-making module with more advanced techniques, such as fuzzy logic, probabilistic models, or decision support systems, could also enable the generation of more complex risk assessment scenarios.

From a user perspective, the system may be further developed to adapt the interface to the needs of different user groups—from crisis management services and local administrations to farmers and individual flood-threatened residents. It is also worth considering the application of the system in a broader environmental context—for example, for monitoring wetlands, water retention, or land cover changes.

In conclusion, the developed solution provides a solid foundation for further research and development work, while its full implementation will require multi-stage testing, validation, and integration with other spatial information systems and flood risk management frameworks.

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