INTELLECTUAL PROCESSING OF GEOSPATIAL AND GEODETIC DATA IN MUNICIPAL MANAGEMENT SYSTEMS

Monograph

Serhii Nesterenko, Oleksandra Baistruk, Kostiantyn Musiienko, Oleksandr Frolov

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Authors:
Nesterenko S., ORCID: 0000-0001-5124-9728
Baistruk O., ORCID: 0009-0009-4458-4929
Musiienko K., ORCID: 0009-0006-2811-1054
Frolov O., ORCID:0009-0003-6968-5714

Reviewers:
Oleksandr Gorb, Candidate of Technical Sciences, Associate Professor, Director of NAVIGATION AND GEODETIC CENTER LLC. Kharkiv, Ukraine

Mykhailo Bahin, Candidate of Technical Sciences, Associate Professor, Deputy Mayor for Executive Affairs, Pivdenne Urban Community, Kharkiv District, Kharkiv Region, Ukraine

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SUMMARY

The monograph is devoted to a comprehensive study of the intellectual processing of geospatial and geodetic data in municipal management systems and the formation of scientifically sound approaches to the creation of a new generation of intelligent geoinformation systems. The work defines the theoretical, architectural and algorithmic foundations for the integration of artificial intelligence into the spatial environment of territorial communities, and substantiates the role of machine learning, deep neural networks, sensor technologies and digital twins in the development of urban management systems. A generalised conceptual model is presented, demonstrating the interaction of key technological layers: geodata, AI models, IoT systems, edge AI and cloud services.

In terms of structure and function, it is proven that an intelligent municipal GIS should include a number of interconnected modules that provide a complete cycle of spatial analytics:

1. A spatial data module that combines geodetic measurements (GNSS, total station surveying, levelling), satellite imagery, remote sensing data, LiDAR scanning, cadastral and registry sets, as well as sensor network data.

2. An analytical module that performs classification, segmentation, forecasting, reconstruction, and anomaly detection using CNN, LSTM, GNN, ConvLSTM, and other types of neural models.

3. A real-time streaming data processing module with the ability to integrate data from IoT, monitoring systems, and operational observations.

4. A module for interacting with Big Data environments, cloud platforms, edge AI devices, and the national geospatial data infrastructure.

5. Visualisation and decision support module based on Smart City Dashboard, which provides multi-level data display, modelling of territory development scenarios, risk assessment and urban environment monitoring.

A concept of a geo-analytical conveyor has been developed, within which a full cycle of work with geodata is carried out: its receipt, cleaning, coordination, modelling,

forecasting and interactive visualisation. It has been proven that the quality of geodetic data, measurement accuracy, topological correctness, and timely updating of spatial information are key factors in the effectiveness of AI models in municipal management.

Empirical results have demonstrated the feasibility of using LSTM models to predict changes in the urban environment, including traffic, development, loads on engineering networks, and environmental indicators. The potential of ConvLSTM and GNN for modelling complex spatio-temporal structures, constructing three-dimensional surfaces, analysing infrastructure connections, and forming digital twins of territories has been revealed. An architecture for an adaptive intelligent GIS based on a microservice approach, cloud-edge technologies, and support for Google Earth Engine, Azure GeoAI, IBM PAIRS, and open GIS environments is proposed.

The monograph also analyses international experience in the use of intelligent GIS in urban management and describes the practices of the world's leading Smart City ecosystems and Ukrainian digital initiatives. The results obtained can be used to develop strategies for the digital transformation of local communities in Ukraine, improve spatial management systems, increase the efficiency of municipal services, form open geodata policies, and implement intelligent GeoAI solutions in the practice of territorial development.

Keywords: geospatial data; geodetic data; municipal geoinformation systems; intelligent processing; artificial intelligence; neural networks; deep learning; LSTM; urban environment forecasting; digital twin; Smart City; GeoAI; remote sensing; territorial communities.

TABLE OF CONTENTS

ABBREVIATIONS AND NOTATIONS

AI – artificial intelligence;

ANN – artificial neural network;

CNN – convolutional neural network;

RNN – recurrent neural network;

LSTM – long short-term memory network;

ConvLSTM – convolutional long short-term memory network;

GNN – graph neural network;

DNN – deep neural network;

ML – machine learning;

DL – deep learning;

GeoAI – geospatial artificial intelligence;

GIS – geographic information system;

SDI – spatial data infrastructure;

IoT – Internet of Things;

Edge AI – artificial intelligence processing performed on edge devices;

Cloud AI – artificial intelligence executed within cloud computing infrastructures;

Big Data – high-volume, high-velocity, high-variety datasets for advanced analytics;

RS – remote sensing;

LiDAR – light detection and ranging;

UAV – unmanned aerial vehicle (drone);

GNSS – global navigation satellite system;

DEM – digital elevation model;

DTM – digital terrain model;

DSM – digital surface model;

DTP – digital twin of a city or infrastructure system;

API – application programming interface;

GPU – graphics processing unit for parallel computing in AI models;

CPU – central processing unit;

ETL – extract, transform, load data-processing pipeline;

WMS – Web Map Service;

WFS – Web Feature Service;

WMTS – Web Map Tile Service;

OGC – Open Geospatial Consortium;

INSPIRE – Infrastructure for Spatial Information in the European Community;

LADM – Land Administration Domain Model;

DBMS – database management system;

PostGIS – spatial database extender for PostgreSQL;

Earth Engine – Google platform for planetary-scale geospatial analysis;

ArcGIS – geographic information system software developed by Esri;

QGIS – open-source geographic information system platform;

Smart City – urban development concept integrating ICT, GIS and IoT;

Smart City Dashboard – geospatial visualization and analytics platform for real-time monitoring of urban indicators;

GIS+AI pipeline – automated workflow integrating geospatial data processing with AI-based modeling;

CRF – conditional random field used for spatial boundary refinement;

Seq2Seq – sequence-to-sequence deep learning architecture;

API Gateway – service for managing interaction between distributed GIS/AI modules;

Sensor Hub – system for aggregating data from IoT devices;

TLS – terrestrial laser scanning;

RTK – real-time kinematic satellite positioning method;

NLP – natural language processing;

EDA – exploratory data analysis;

KPI – key performance indicator in municipal governance.

INTRODUCTION

The current stage of territorial management development is characterised by profound structural changes related to the digitisation of management processes, decentralisation of powers, and the growing role of spatial information in shaping management decisions. In these conditions, geographic information systems (GIS) are transforming from tools for storing and visualising cartographic information into comprehensive information and analytical platforms capable of integrating heterogeneous geospatial and geodetic data, performing multi-level analysis and providing decision support in near real time [1].

The key resource for digital municipal management is geospatial and geodetic data generated on the basis of satellite navigation systems (GNSS), remote sensing of the Earth, unmanned aerial vehicles, laser scanning, Internet of Things sensor networks, as well as cadastral, registry and urban planning information systems. The rapid growth in the volume of such data, its heterogeneity in terms of structure, accuracy, spatial resolution and update frequency significantly complicate the application of traditional office-based processing methods focused on manual or semi-automated procedures [2].

Recent scientific studies emphasise that classical approaches to processing geodetic measurements and spatial data do not meet the modern requirements of municipal geoinformation systems, especially in the context of implementing Smart City concepts and digital twins of territories. The main problems remain the presence of random and systematic errors, noise in measurements, topological inconsistency of spatial layers, differences in coordinate systems and data storage formats, as well as the complexity of integrating the results into a single information environment of the territorial community [3].

One of the most promising approaches to solving these problems is the use of artificial intelligence and machine learning methods, which have proven their effectiveness in analysing large multidimensional data sets, automatic classification, segmentation, forecasting and process optimisation. In combination with geoinformation technologies, these methods form the interdisciplinary field of GeoAI, which is

considered a new paradigm for spatial analysis and territorial development management [4].

The stage of preliminary processing of geodetic and geospatial data is of particular importance in the context of the intellectualisation of municipal GIS, as it determines the quality of further analysis and the reliability of machine learning results. It is at this stage that noise filtering, parameter normalisation, coordinate system transformation, spatial structure harmonisation and training sample formation for intelligent models are carried out. As recent studies show, the effectiveness of machine learning algorithms in spatial tasks critically depends on the quality and representativeness of the input geodata [5].

In the context of decentralised management and the growing role of local communities, the issue of intellectual processing of geodetic and geospatial data is becoming particularly important for solving practical problems of infrastructure monitoring, land use, environmental status, transport accessibility and spatial development. The integration of artificial intelligence methods into municipal geoinformation systems allows a transition from reactive management to a proactive, scenario-based and predictive approach, which is in line with current international trends in the development of digital governance[6].

Thus, the relevance of this monograph is determined by the need for a comprehensive scientific understanding of methods for processing geodetic and geospatial data using artificial intelligence in municipal management systems. The approach proposed in this work is focused on covering the entire geospatial analysis pipeline — from data sources and pre-processing to the integration of intelligent models into the structure of municipal GIS and decision support systems, which allows for the formation of a comprehensive methodological framework for the implementation of intelligent geoinformation solutions in the practice of territorial development.

An analysis of current scientific publications shows that the application of geoinformation systems, spatial analysis and artificial intelligence methods is actively developing in the global scientific community. The works of foreign researchers consider the issues of the architecture of intelligent urban platforms, the construction of GeoAI

conveyors, the integration of machine learning with spatial databases, and the use of neural network models for the analysis of satellite and sensor data [1, 4].

At the same time, a significant part of the research focuses mainly on the analytical or visualisation level of GIS, while the issue of systematic processing of geodetic data — as the primary basis for geoinformation models — remains fragmentarily covered. In scientific works devoted to Smart Cities and digital twins of cities, geodetic measurements are often considered as a secondary source of data, without proper analysis of the specifics of their errors, methods of office processing and integration into intelligent algorithms. [3]. This leads to a scientific gap between theoretical GeoAI models and the practical needs of geodetic support for municipal geoinformation systems.

The object of research in this monograph is the processes of formation, processing and use of geodetic and geospatial data in municipal management systems.

The subject of the study is the methods of preliminary and intellectual processing of geodetic and geospatial data using artificial intelligence technologies in the structure of municipal geoinformation systems.

The aim of the monograph is to scientifically substantiate and develop a comprehensive approach to the processing of geodetic and geospatial data using artificial intelligence methods in order to improve the efficiency of municipal geoinformation systems and the quality of management decisions made by local communities.

To achieve this goal, the monograph sets out to solve the following tasks:

- analyse the role of geodetic and geospatial data in modern digital territorial management systems;

- investigate the sources of geodetic and spatial data formation in municipal GIS and the problems of their quality;

- systematise methods of preliminary office processing of geodetic data in GIS and CAD environments;

- substantiate the possibilities of applying artificial intelligence methods to automate the processing of geodetic measurements;

- develop approaches to integrating intelligent data processing into the architecture of municipal geoinformation systems;

- identify applied scenarios for the use of intelligent geodata processing in territorial communities.

The theoretical and methodological basis of the study is the provisions of the theory of geographic information systems, spatial analysis, the theory of geodetic measurement errors, the concept of digital twins of territories, as well as methods of artificial intelligence and machine learning. The work applies systematic, informational, and spatial-analytical approaches, methods of mathematical and statistical analysis, intellectual classification, and modelling, which corresponds to current trends in the development of GeoAI technologies [2].

The scientific novelty of the monograph lies in:

- forming a holistic approach to the processing of geodetic data as a key element of intelligent municipal GIS;

- substantiating the role of preliminary office processing of geodetic measurements in improving the effectiveness of artificial intelligence methods;

- the development of the concept of integrating intelligent algorithms into the geoinformation pipeline of municipal management systems;

- the combination of geodetic methods, GIS technologies and artificial intelligence in a single methodological framework.

The practical significance of the results obtained lies in the possibility of using the materials of the monograph in the creation and modernisation of municipal geoinformation systems, automating the office processing of geodetic data, developing intelligent decision support modules for territorial communities, as well as in the educational process during the training of specialists in the specialty G18 'Geodesy and Land Management'.

The monograph consists of an introduction, five chapters, which sequentially consider the theoretical and applied aspects of processing geodetic and geospatial data using artificial intelligence, conclusions, a list of sources used, and appendices.

1   GEOSPATIAL AND GEODETIC DATA IN DIGITAL MUNICIPAL MANAGEMENT SYSTEMS

1.1   The role of geospatial and geodetic data in modern territorial management

Geospatial and geodetic data form the foundation of information support for modern territorial management, as they allow for the formalisation of the spatial characteristics of objects and processes occurring within territorial communities. In municipal management systems, space is not only the environment in which infrastructure is located, but also an active factor in socio-economic development, environmental safety and the quality of life of the population. Accordingly, management decisions require an accurate, up-to-date and systematic spatial representation of the territory, which is provided by means of geodetic measurements and geoinformation technologies [7].

In the classical sense, geodetic data reflects the results of measurements of the position, shape and dimensions of objects on the Earth's surface, performed in a specific coordinate and elevation system. They form the basis for the creation of topographic plans, digital terrain models, engineering and geodetic networks, cadastral systems and urban planning documentation. Geospatial data, in turn, covers a wider range of information, combining geometric, attributive and temporal characteristics of objects and phenomena, which allows the territory to be viewed as a multidimensional dynamic system [8].

In modern territorial management, geospatial data serves as an integration core, providing a means of combining information from various sectors, including land use, transport, engineering infrastructure, ecology, demography, and socio-economic development. The spatial dimension allows heterogeneous data sets to be combined in a single coordinate system and comprehensive analysis of territorial processes to be carried out. As noted in works on digital governance, spatially oriented data significantly improves the soundness of management decisions, as it allows for the

consideration of territorial interrelationships, zones of influence, and spatial constraints [2].

Geodetic data is particularly important in the context of decentralisation of management and the transfer of a significant part of powers to local communities. Local authorities are responsible for spatial planning, land resource management, engineering infrastructure development, construction control and monitoring of the state of territories. All these functions are impossible without a reliable geodetic basis that ensures the accuracy of spatial decisions and the consistency of various information resources [9].

In municipal geographic information systems, geospatial and geodetic data form the base layer, onto which thematic information layers and analytical results are superimposed (fig. 1.1). Digital topographic plans, relief models, orthophoto plans, and cadastral maps form the geometric basis of GIS, while attribute data provide semantic content for spatial objects. The combination of these components enables spatial analysis, scenario modelling of territorial development, and support for management decision-making [10].
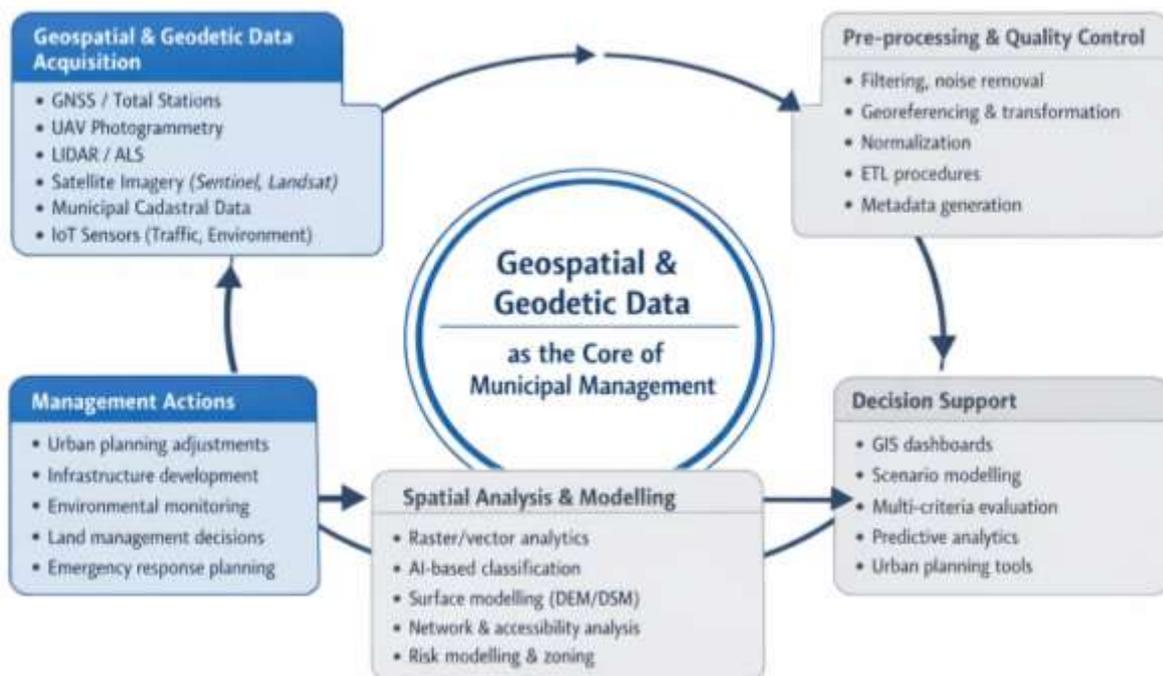
Fig. 1.1 — Geospatial and geodetic data in the territorial management cycle

In modern conditions, the role of geospatial data is growing significantly due to the transition from static models of territory to dynamic ones focused on analysing changes over time. Remote sensing data, GNSS observations, sensor networks and mobile information sources enable continuous monitoring of the state of territories, infrastructure and the environment. This, in turn, creates the conditions for the implementation of digital twin concepts, in which geodetic and geospatial data serve as the basis for building virtual models of real space [11].

At the same time, the growing role of geospatial data in territorial management places increased demands on its quality, consistency and processing speed. [12]. Management decisions based on incorrect or outdated geodetic data can lead to planning errors, inefficient use of resources and socio-economic losses. This necessitates the development of methods for processing, quality control and intelligent analysis of geodetic and geospatial data as a key element of modern municipal geoinformation systems.

1.2 Classification of sources of geodetic and spatial data in municipal systems

The functioning of modern municipal geoinformation systems is based on the use of a wide range of geodetic and geospatial data from diverse sources that vary in accuracy, scale, timeliness, and method of formation. The classification of such sources is a prerequisite for building an effective geodata management system, as it allows determining the role of each type of data in the structure of a municipal GIS, justifying methods for their processing and integration, and assessing the limitations and risks associated with the use of specific information resources. [13].

Scientific literature emphasises that territorial management systems are characterised by multiple sources of geospatial information, which is due to both the diversity of municipal management tasks and the evolution of data collection technologies [8]. Within municipal GIS, it is advisable to classify geodetic and spatial

data according to origin, acquisition technology, level of spatial detail and functional
purpose (fig. 1.2).
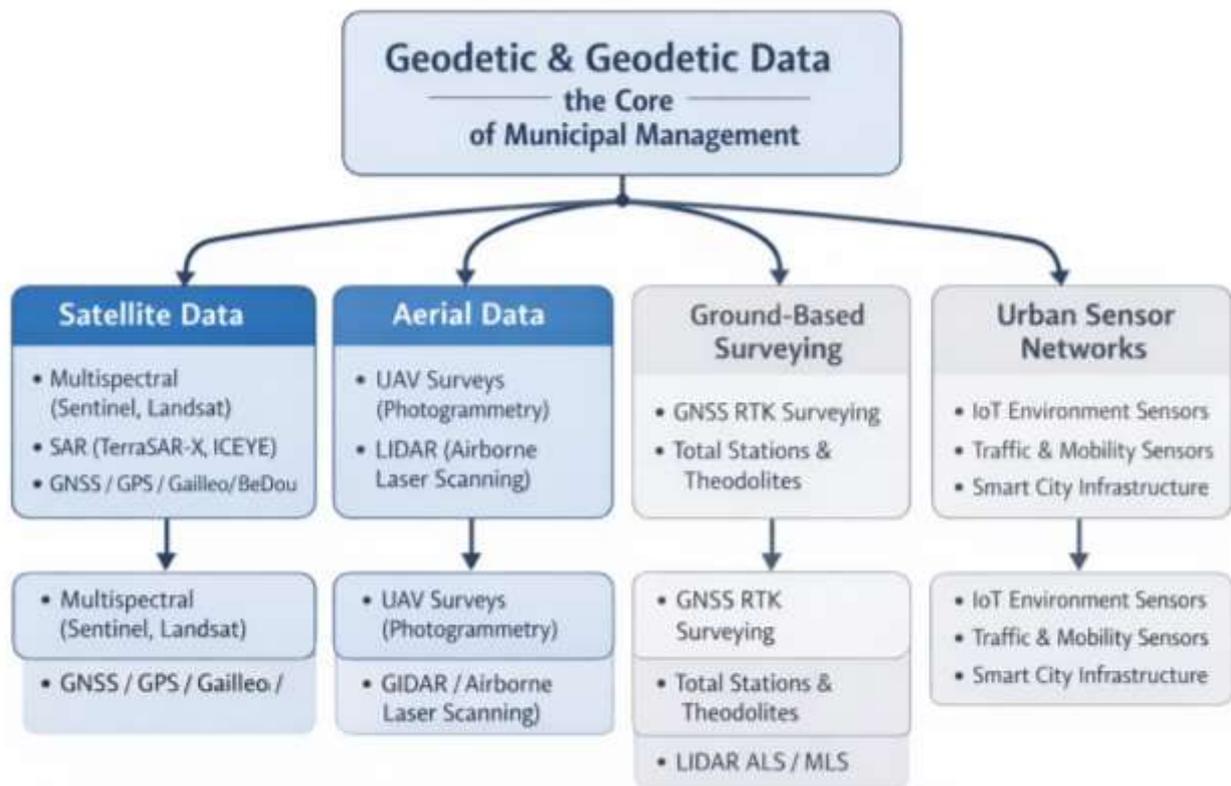
*Fig. 1.2 — Classification of geodetic and geospatial data sources in municipal
GIS*

The first and basic group consists of geodetic measurement data generated as a
result of field work using classical and satellite geodetic methods. This group includes
the results of GNSS observations, materials from tacheometric surveys, levelling,
engineering and geodetic surveys, as well as data from local and state geodetic
networks. [14]. This data is characterised by high metric accuracy and forms the basis
for the creation of topographic plans, digital terrain models and the spatial basis of
municipal GIS. In the context of territorial management, geodetic data acts as a
reference layer, ensuring the consistency of all other geoinformation resources [15].

The second group consists of remote sensing data obtained using satellite and
aerial photography systems. Satellite images of various spatial resolutions (Sentinel,
Landsat, WorldView, etc.) are widely used in municipal GIS for monitoring

development, analysing land use, assessing environmental conditions, and identifying changes in the territory over time. Aerial photography using unmanned aerial vehicles allows for the creation of detailed orthophotomaps and three-dimensional models of individual urban development areas with high spatial accuracy, which is particularly important for local management tasks [16].

Laser scanning (LiDAR) data occupies a special place among geospatial data sources, allowing the creation of highly accurate digital models of terrain and surface, as well as three-dimensional models of buildings. In municipal systems, such data is used to analyse building density, assess flood risks, model insolation, analyse visibility, and create digital twins of territories. High point density and the possibility of automated processing make LiDAR data an important source of information for intelligent GIS [17].

The next group consists of cadastral, registry and urban planning data generated within state and municipal information systems. This includes information about land plots, real estate objects, functional zoning of territories, urban planning regulations, and restrictions on land use. [18]. Such data has a pronounced legal and semantic character and is critical for land use management, territorial development planning, and building control. At the same time, it often varies in terms of relevance and spatial consistency, which complicates its integration with geodetic and remote sensing data [19].

In modern municipal GIS, data from sensor networks and the Internet of Things (IoT) are becoming increasingly important, providing spatially referenced data in near real time. This group includes data on traffic flows, resource consumption, the state of engineering networks, and air and noise pollution levels. Such data is highly dynamic and involves a large number of records, which necessitates the use of automated and intelligent processing methods [5].

Voluntarily collected geographic information (VGI) and open geospatial resources, such as OpenStreetMap, constitute a separate category. Such data plays a supporting role in municipal GIS, especially when official sources are limited or information needs to be updated quickly [20]. At the same time, its use requires careful

validation and quality control, as the level of accuracy and reliability can vary significantly [21].

Thus, sources of geodetic and geospatial data in municipal systems form a complex multi-level structure in which each type of data performs a specific function and has its own limitations. Effective territorial management is only possible with the comprehensive use of these sources, their spatial and semantic consistency, and the application of modern processing methods capable of working with heterogeneous and large-scale geodata sets.

1.3 Structure and properties of geodata: accuracy, completeness, relevance, consistency

Geospatial and geodetic data used in municipal geoinformation systems have a complex multidimensional structure that determines the possibilities for their further analysis and practical use in territorial management systems. [22]. Unlike traditional tabular or textual data, geodata combines geometric, attributive and temporal components that form a spatio-temporal model of the territory (Fig. 1.3). It is this integrated structure that determines the specific requirements for the quality of geodata and necessitates the use of specialised methods for its control and processing [8].

Fig. 1.3 — Key properties of geodetic and geospatial data in municipal GIS and their impact on the quality of management decisions

The geometric component, which determines the position of objects in space and the form of their representation, occupies a central place in the structure of geospatial data. [23]. It can be implemented in the form of vector models (points, lines, polygons), raster representations, or three-dimensional models of surfaces and objects. For geodetic data, the geometric component is formed on the basis of measurement results in specific coordinate and elevation systems, which imposes strict requirements on metric accuracy and unambiguity of spatial position. [15].

Equally important is the attribute component of geodata, which provides a semantic description of spatial objects and processes. Attribute information may include legal characteristics of land plots, functional purpose of territories, technical parameters of engineering networks, environmental indicators, and socio-economic indicators. In municipal GIS, attribute data often comes from different information systems and varies in structure and degree of formalisation, which complicates its harmonisation and integration with geometric models [10].

The temporal component of geodata becomes particularly important in the context of the transition to dynamic models of territory. The relevance of data, the frequency of its updates, and the ability to analyse changes over time are key factors in the effectiveness of municipal management. Remote sensing data, sensor networks, and GNSS observations allow for the monitoring of territorial processes in real or quasi-real time, opening up new opportunities for forecasting and scenario analysis [2].

One of the key properties of geodata is accuracy, which characterises the degree of correspondence between the spatial position of objects and their actual location on the ground. For geodetic data, accuracy is determined by measurement methods, instrument characteristics, observation conditions and the processing algorithms used. In municipal GIS, the accuracy of geodata directly affects the quality of spatial decisions, particularly in planning development, locating utility networks, and defining land parcel boundaries. Insufficient accuracy can lead to the accumulation of errors and conflicts between spatial layers [24].

Another important property is the completeness of geodata, which reflects the degree of coverage of the territory and objects of study. Incomplete data may be the

result of limited information sources, uneven surveys, or the lack of updates for certain areas. In territorial management systems, incomplete geodata complicates comprehensive analysis and may distort modelling results [25]. Therefore, ensuring data completeness is one of the key tasks at the stage of developing municipal geoinformation systems [19].

The relevance of geodata is determined by the correspondence of information to the actual state of objects and processes at the time of its use. In dynamic conditions of territorial development, even highly accurate data can quickly lose its value if it is not regularly updated. This is especially true for urban development, transport infrastructure and engineering networks, where changes occur constantly. The use of automated methods of data collection and processing, as well as the integration of sensor networks and remote sensing, allows for increasing the relevance of geospatial information in municipal GIS [9].

An equally important characteristic of geodata is its consistency, which reflects the degree of correspondence between different data sets in terms of geometry, attribute content and time parameters. In municipal systems, situations often arise where data from different sources have differences in coordinate systems, scales, or classification schemes. Lack of consistency complicates data integration and can lead to errors in spatial analysis. Therefore, the issues of geodata harmonisation and the application of interoperability standards are of particular importance [25].

Thus, the structure and properties of geodetic and geospatial data determine their suitability for use in municipal geographic information systems. Ensuring high accuracy, completeness, relevance and consistency of geodata is a prerequisite for effective territorial management and creates the basis for the further application of intelligent analysis and modelling methods.

1.4. Problems of geodetic data quality in digital GIS

The quality of geodetic data is one of the key factors determining the effectiveness of digital geographic information systems and the reliability of

management decisions in the field of territorial management. In municipal GIS, geodetic data serves as the basis for the integration of thematic layers, spatial analysis and modelling of territorial development.[27]. At the same time, in the process of collecting, processing and integrating geodetic information, a number of problems arise related to measurement errors, noise, data gaps and topological conflicts between spatial objects, which significantly complicates the use of such data in digital GIS (fig. 1.4) [25].
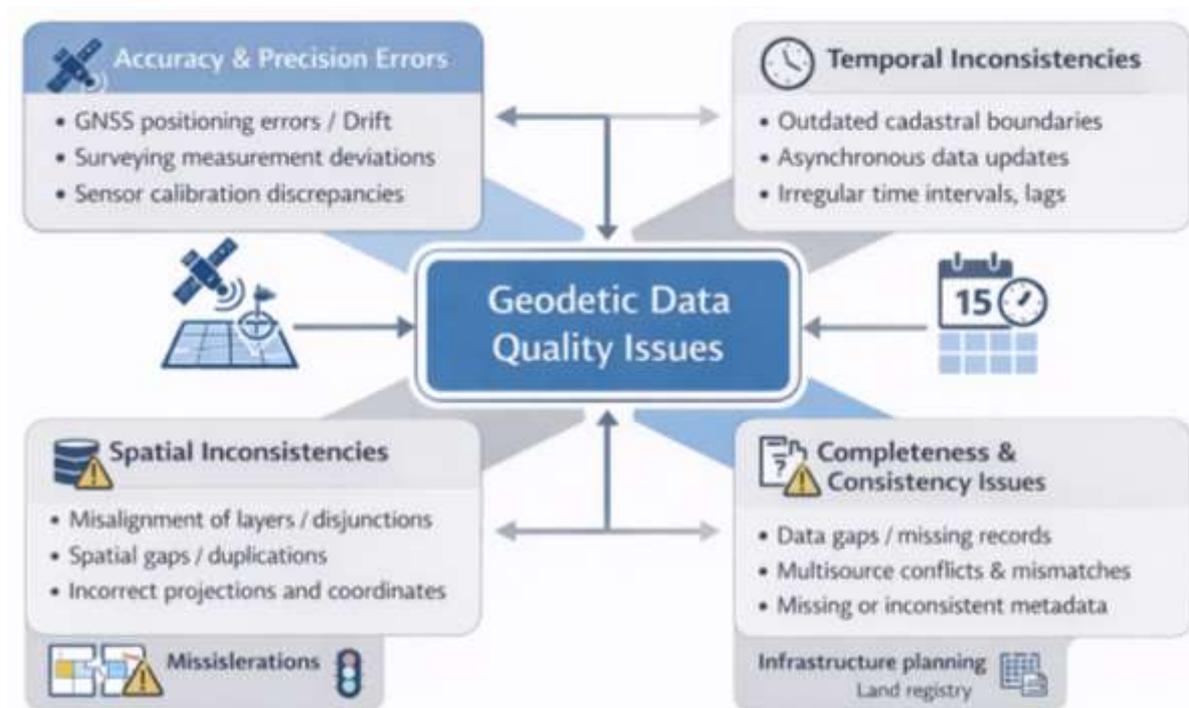
Fig. 1.4 — Main types of geodetic data quality problems in digital GIS and their manifestations

Geodetic data errors are an objective consequence of the measurement process and can be either random or systematic in nature. The main sources of errors include limitations in the accuracy of geodetic instruments, the influence of atmospheric conditions, multipath effects in satellite observations, inaccuracies in the centring and orientation of instruments, as well as errors related to the human factor. In digital GIS, such errors manifest themselves in the form of displacement of spatial objects,

distortion of geometry, and inconsistencies between data obtained from different sources [15].

A separate problem is the presence of noise in geodetic data, which is particularly characteristic of arrays obtained as a result of GNSS observations, laser scanning and remote sensing of the Earth. Noise can be caused by random signal fluctuations, interference from buildings, vegetation or terrain, as well as the characteristics of primary processing algorithms. In digital GIS, the presence of noise complicates automated data analysis, leads to the appearance of artefacts in digital terrain and surface models, and reduces the effectiveness of further application of machine learning methods [17].

An important problem affecting the quality of geodetic data in digital GIS is the gaps and fragmentation of spatial information that arise as a result of incomplete coverage of the territory by surveys, varying frequency of data updates, or limited access to certain information resources. [28]. Such gaps are particularly characteristic of municipal systems, where geodata is formed gradually, in different years and by different organisations. The presence of fragmented data complicates comprehensive spatial analysis and can lead to distortion of the results of territorial development modelling [19].

A significant problem in integrating geodetic data into digital GIS is topological conflicts that arise when combining different spatial layers. Such conflicts include overlapping polygons, breaks in linear objects, mismatches between adjacent areas, incorrect intersections of engineering networks, and other violations of topological rules. [29]. Topological errors can be the result of varying accuracy of source data, differences in survey scales, or incorrect transformation of coordinate systems. In municipal GIS, such conflicts not only complicate spatial analysis, but can also have legal and economic consequences, particularly in the areas of land use and urban planning [10].

Problems with the quality of geodetic data are exacerbated in the context of multi-source municipal GIS, where data of different origins, accuracy and formats are combined. The lack of uniform standards for quality description, metadata and

validation procedures leads to the accumulation of errors in geoinformation databases. As noted in the recommendations of international organisations, geodata quality management should be an integral part of the life cycle of geoinformation systems, starting with the data collection stage and ending with their use in decision support systems [9].

Thus, problems of errors, noise, gaps, and topological conflicts are systemic for digital geoinformation systems and require the use of comprehensive methods of quality control and processing of geodetic data. Awareness of these problems and their detailed analysis is a necessary prerequisite for the transition to the use of intelligent processing methods capable of automating the detection and correction of errors in large geodetic information arrays.

1.5 Geodata as the basis for management decisions in local communities

In the modern system of local community management, geodetic and geospatial data play a decisive role, as they provide spatial specificity to management processes and form the information basis for decision-making at the strategic, tactical and operational levels. Any management action related to the development of the territory, the use of land resources, the location of infrastructure facilities or the provision of environmental safety has a spatial reference, without which its full justification is impossible. In this context, geodata is not only a source of information, but also a tool for formalising management logic, allowing a transition from intuitive decisions to scientifically based territorial management [2].

Geodetic data obtained as a result of topographic and geodetic works, GNSS observations and engineering surveys form the spatial basis for management models of territorial communities. They ensure the metric accuracy of spatial decisions, which is critically important when determining the boundaries of administrative-territorial entities, land plots, functional use zones, and development objects.[30]. On this basis, urban planning documents, master plans, zoning plans and detailed plans for territories are formed, which directly influence the socio-economic development of communities.

Visualisation of these processes in a geoinformation environment allows you to track the full cycle of management decision-making — from the analysis of initial information to the implementation of planned measures (fig. 1.5) [10].

At the level of land resource management, geospatial data provides the possibility of integrated analysis of land use, taking into account legal, economic and environmental aspects. The combination of cadastral information, geodetic surveys and remote sensing data allows for the identification of irrational land use, conflicts between different types of land use, violations of land use regimes and areas with special conditions of use. [31] . In municipal geoinformation systems, such analytical capabilities are transformed into practical decision-making support tools that enable local authorities to exercise spatially informed control and planning of territorial development (fig. 1.5) [19].

Geodata is particularly important in the management of engineering and transport infrastructure development in local communities. Spatial analysis of geodetic and geospatial data allows for the assessment of the accessibility of social infrastructure facilities, the optimisation of engineering network routing, the modelling of transport flows, and the prediction of the consequences of infrastructure projects. In combination with geoinformation dashboards and digital maps, this creates a basis for scenario analysis, allowing community leaders to compare alternative development options and choose the most effective management decisions (fig. 1.5) [1].

Geospatial data also plays a key role in managing environmental safety and emergency risks. Data on relief, hydrological conditions, the state of green spaces, sources of pollution and anthropogenic load allow for the spatial identification of high-risk areas, the modelling of scenarios for the development of hazardous processes and the planning of measures to minimise their consequences. [32]. The integration of geodetic data with the results of remote sensing and sensor observations in municipal GIS creates the conditions for a transition from reactive response to preventive management of territorial risks (fig. 1.5) [9].

In the context of the digitalisation of public administration, geodata is becoming the basis for the formation of decision support systems, in which spatial analysis is

combined with analytical and predictive models. The use of interactive maps, geoinformation dashboards and scenario models not only improves the quality of management decisions, but also ensures their transparency and comprehensibility for a wide range of stakeholders, including representatives of the public. [33]. In this context, geodata performs a communication function, helping to involve citizens in spatial planning and territorial development control processes (fig. 1.5) [7].
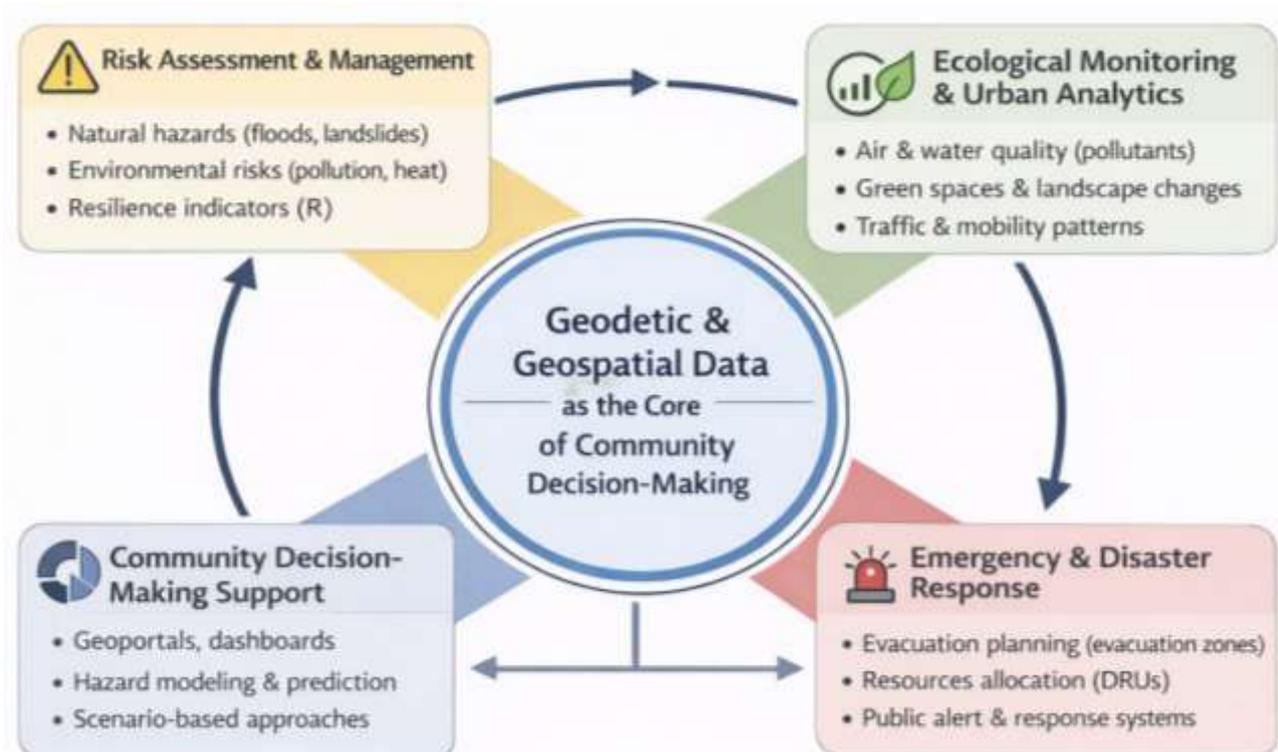
Fig. 1.5 — The role of geodetic and geospatial data in the decision-making cycle of local communities

However, the effective use of geodetic and geospatial data in decision-making is only possible if the data is of high quality, relevant and integrated into a single information environment for the local community. Fragmented data, the lack of agreed standards and insufficient automation of processing significantly reduce the potential of geoinformation systems as a management tool. [34]. This necessitates a transition to intelligent methods of geodata processing capable of automating the analysis of large amounts of information, reveal hidden spatial patterns and provide scientifically sound support for management decision-making in territorial communities, which logically

justifies the further transition to the consideration of methods for the preliminary processing of geodetic data in the next section of the monograph.

1.6 The conceptual role of geodetic and geospatial data in the transformation of municipal GIS

The consideration of the role, sources, structure and quality of geodetic and geospatial data in the previous sections allows us to form a comprehensive understanding of their conceptual significance in modern municipal geoinformation systems. In the context of the digital transformation of territorial management, geodata ceases to be merely a technical resource for the creation of cartographic products and acquires the status of a strategic asset of the territorial community, directly affecting the effectiveness of management decisions, sustainable development and the ability of communities to adapt to socio-economic and environmental challenges. [35].

New-generation municipal geoinformation systems are being developed as complex multi-level information and analytical platforms in which geodetic and geospatial data play an integrative role, combining heterogeneous information flows into a single space-time continuum. [36]. It is the spatial dimension that allows the synchronisation of data on land use, engineering infrastructure, transport, environmental status and socio-economic processes, forming the basis for a comprehensive analysis of territorial development. This approach is in line with modern concepts of integrated geospatial management, which are actively promoted by international organisations and the scientific community [19].

Summarising the results of the analysis, it can be argued that the key feature of modern municipal GIS is their transition from static information systems to dynamic environments for analysis and decision support. In such systems, geodetic data form an accurate metric basis, while geospatial data provide a multidimensional description of the territory, taking into account attributive and temporal characteristics. The combination of these components allows for scenario modelling of territorial

development, assessment of the consequences of management decisions, and forecasting of changes in space and time [2].

At the same time, analysis shows that the effectiveness of such a transformation of municipal GIS is largely limited by problems with the quality of geodetic and geospatial data. Measurement errors, noise, fragmented data, and topological conflicts not only reduce the accuracy of spatial models, but also complicate the implementation of automated and intelligent analysis methods. In this context, geodata quality management takes on conceptual significance and should be considered an integral part of the life cycle of municipal geoinformation systems — from data collection and pre-processing to their use in decision support systems [25].

The relationship between the quality of geodata and the applicability of artificial intelligence methods in municipal GIS deserves special attention. Intelligent algorithms, in particular machine learning and neural network modelling methods, are extremely sensitive to the quality of input data, which necessitates careful pre-processing of geodetic information. Thus, geodetic and geospatial data are not only the object of analysis, but also an active factor that determines the architecture and functionality of intelligent geographic information systems (fig. 1.6) [4].
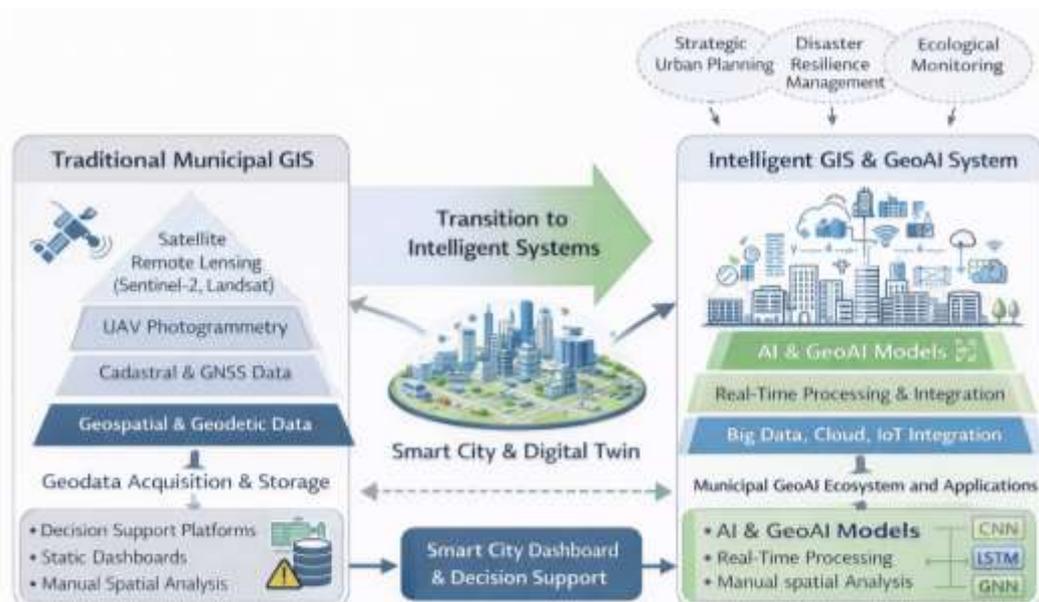
Fig. 1.6 — Conceptual model of the role of geodetic and geospatial data in the transformation of municipal geoinformation systems

To summarise, it can be concluded that geodetic and geospatial data are the conceptual core of the transformation of municipal GIS into intelligent territory management systems. They determine the possibilities for integrating heterogeneous information resources, the level of automation of analytical processes, and the effectiveness of management decisions. That is why the further development of municipal geoinformation systems is impossible without a systematic approach to the preliminary processing of geodetic data, which creates a logical basis for moving on to the consideration of the theoretical and methodological aspects of such processing in the next section of the monograph.

1.7 Regulatory, legal and standard support for geodetic and geospatial data in Ukraine and the European Union

Regulatory, legal and standard support for geodetic and geospatial data forms the structural, technological and methodological basis for the functioning of modern geoinformation systems, defining the principles for the creation, integration and use of spatial information in various areas of territorial management. The harmonised regulatory framework covers international standards, European regulations, UN recommendations and national acts that ensure the interoperability of geodata and the possibility of its use in analytics and intelligent modelling systems [26].

In international practice, the basis for regulatory support is the ISO 19100 series of standards, which regulate the modelling, structure, quality and metadata of geospatial data. The ISO 19115 standard defines the metadata model, mechanisms for documenting data sources and accuracy parameters, while ISO 19157 describes the criteria for assessing the quality of geodata, including logical consistency, completeness and positioning errors [38]. The application of ISO standards enables the integration of geodata into complex multi-component GIS and minimises the risks of source information not meeting the requirements of analytical models.

The Open Geospatial Consortium (OGC) protocols and specifications, which regulate the exchange of geospatial resources in a web environment, play a significant

role in ensuring interoperability. WMS, WFS, WCS, CSW and other services standardise mechanisms for accessing map layers, vector objects, raster coverages and metadata, enabling the integration of data from different sources into a single GIS-oriented environment [39]. Given that municipal GIS are multi-source, OGC specifications are a critical factor in their compatibility and scalability.

The key regulatory document for European Union countries is the INSPIRE Directive, adopted with the aim of creating an integrated spatial data infrastructure for Europe. INSPIRE defines mandatory geodata themes, metadata structure, data model harmonisation schemes and exchange formats, ensuring the uniformity of spatial information across the EU [40]. For Ukraine, INSPIRE is a basic guideline in the process of harmonising the national geodata infrastructure with European standards within the framework of digital integration.

Global approaches to the development of geospatial infrastructures are being formed within the United Nations Committee of Experts on Global Geospatial Information Management (UN-GGIM) initiative, which defines strategic positions on geodata management, standardisation, coordination and integration of spatial resources in public administration. UN-GGIM develops approaches to multi-level geodata exchange, national infrastructure management and the use of spatial information for sustainable development purposes [9]. The UN-GGIM recommendations are important for municipal GIS because they define long-term models of data interaction between local communities, government agencies, and international platforms.

Ukraine's national legislation in the field of geodesy and geoinformatics includes the laws 'On National Geospatial Data Infrastructure,' 'On Topographic, Geodetic and Cartographic Activities' and 'On the State Land Cadastre', which define the principles for the creation, maintenance and exchange of spatial resources at the state and municipal levels. The legislative framework is harmonised with European approaches and provides for the openness, standardisation and interoperability of geodata, creating conditions for the effective functioning of local geoportals, municipal GIS and digital analytical platforms [41].

A separate area of regulatory support concerns open data, in particular the management of spatial information in machine-readable formats. The Law on Access to Public Information and resolutions of the Cabinet of Ministers of Ukraine on the list of open datasets define geospatial data as high priority, obliging authorities to ensure their publication in a standardised format and to keep them up to date [42]. The openness of geodata creates the basis for its integration into geoanalytical services, digital twins of territories, and intelligent monitoring systems.

Thus, regulatory and standard support defines a comprehensive platform for the formation of high-quality, harmonised and interoperable geospatial data necessary for the functioning of modern municipal GIS. Compliance with ISO and OGC standards, INSPIRE directives and UN-GGIM recommendations enables the scaling of geoinformation resources and their use in analytical models, forecasting and intelligent data processing, forming the basis for the development of a new generation of intelligent geoinformation systems.

An important component of regulatory support is the standards for the organisation, storage and structuring of geodata in national and municipal geoinformation systems. In modern practice, standardised data models focused on compatibility between different sectors of land management — land cadastre, engineering infrastructure, environmental monitoring systems, transport networks and spatial registers — are becoming increasingly important. One of the key areas is the implementation of data models that comply with the UML, GML and CityGML concepts, which provide a formalised description of the geometry and attributes of objects, as well as their interrelationships in the urban environment [43]. The use of these models in conjunction with OGC specifications creates the conditions for building integrated digital twins of territories, which are becoming a key tool for strategic territorial planning.

In the field of spatial registers and cadastral systems, an extensive regulatory framework has also been established, defining the rules for coding, maintaining and harmonising spatial information. Many EU countries use a unified cadastral data model that integrates the legal, geometric and attributive characteristics of land parcels and

real estate objects. In Ukraine, similar approaches are laid down in regulatory documents governing the maintenance of the State Land Cadastre, but the process of harmonisation with European requirements is ongoing. Recent studies highlight the need to move from fragmented models to semantically consistent data structures that enable the creation of comprehensive new-generation cadastral and registration systems [44]. The implementation of international models such as LADM (ISO 19152) makes it possible to minimise discrepancies between different sets of cadastral and urban planning data, ensure their relevance and maintain compatibility with engineering GIS.

Technological standards for database structure and geoportal management systems have a significant impact on the formation of national geospatial infrastructure. In particular, the creation of municipal geoportals requires compliance with requirements for accessibility, scalability, security, and mechanisms for updating and storing geodata. Research in the field of geospatial data infrastructure emphasises the importance of using service-oriented architecture (SOA), which allows the creation of modular systems that are easily adaptable to new sources of information and types of services [45]. In municipal GIS, such approaches enable the rapid integration of new data sets, the connection of sensor monitoring platforms, and support for intelligent analytical tools that work with data in real time.

In the context of the rapid development of Earth remote sensing technologies, the regulatory framework governs the licensing, access and use of satellite images, as well as the requirements for their geometric and radiometric correction. Modern satellite platforms — Sentinel, Landsat, WorldView, PlanetScope — generate large amounts of data that require a standardised approach to processing. Regulatory recommendations from NASA, ESA and other agencies provide for standard correction procedures (L1C, L2A), which ensure data uniformity and the possibility of their integration into GIS without additional high-level transformations [46]. Regulatory requirements for preliminary processing of remote sensing data are fundamentally important for integrating satellite information into intelligent models of urban

processes — from building analysis to monitoring the environmental status of territories.

Standards and regulatory requirements in the field of urban monitoring sensor network management are becoming increasingly important. The Internet of Things (IoT), networks of sensors for air quality, traffic, noise pollution, and the state of engineering communications are forming a new type of geospatial information, characterised by high update frequency, format diversity, and the stochastic nature of data. The standards governing their integration into geoinformation systems include OGC SensorThings API specifications and real-time standards that provide a unified format for accessing sensor platform data [47]. For municipal GIS, the integration of sensor networks is critically important, as it ensures the relevance of data for forecasting models and machine learning algorithms.

A separate category of regulatory documents consists of rules for security, personal data protection, and information compatibility in digital infrastructures. Since a significant portion of geospatial information is related to engineering networks, critical infrastructure, and personalised territorial attributes, cybersecurity regulations define the principles of data anonymisation, communication channel protection, and access segmentation. EU countries apply GDPR requirements that regulate the processing of spatial data that may contain personalised information. Studies emphasise the need to create specialised policies for managing access to geodata, especially in municipal systems where a large number of heterogeneous sources are integrated [48]. Such requirements become particularly important in the context of using intelligent algorithms that can automatically detect hidden patterns in users' spatial behaviour.

In summary, regulatory documents and geospatial data standards form a multi-level regulatory system that encompasses international recommendations, European directives and national acts of Ukraine. They ensure the uniformity, quality, interoperability, and security of geospatial data, which is the foundation for building modern municipal GIS, integrated monitoring systems, and intelligent spatial analysis platforms. It is the standardised regulatory framework that makes it possible to apply

machine learning and artificial intelligence methods, implement the concept of digital twins of territories and form technologically mature geoinformation infrastructures.

It is important to emphasise that the regulatory framework for geodata in EU countries is largely aimed at unifying the procedures for exchanging spatial information between different departments and authorities, which allows for the formation of integrated information systems on a pan-European scale. INSPIRE has introduced a model that has gradually transformed geospatial resources from local, departmental datasets into interconnected spatial clusters capable of meeting the analytical needs of EU environmental, transport, infrastructure, land and urban policy [49]. Ukraine, in the process of gradually approaching EU standards, is integrating INSPIRE provisions and international standards into the structure of the NIGD, which is a strategic direction for the development of digital governance.

Particular attention should be paid to the regulatory aspects governing the storage and updating of geospatial resources. International practice requires data version control, change tracking, and the availability of historical states of spatial objects, which allows for retrospective analysis of territorial development. Such approaches are laid down in a number of ISO 19100 standards and are actively used in environmental monitoring, cadastral systems, and transport analytics [50]. For Ukrainian municipal GIS, this means the need for a gradual transition from static cartographic materials to dynamic databases that store the state of the territory in a time dimension and can be integrated into intelligent forecasting systems.

Numerous international studies emphasize that spatial data systems created in accordance with ISO and OGC standards are significantly more effective in the context of implementing analytical platforms and artificial intelligence algorithms. Such systems reduce the number of semantic conflicts, simplify the modeling of relationships between objects, and improve the quality of input features for machine learning [51]. This is particularly important for municipal GIS, where geospatial data is often collected by different services and has a heterogeneous structure, different coordinate systems, and varying levels of accuracy and completeness.

At the level of national legislation in Ukraine, an important component of regulatory and legal support is the approved instructions and methodologies for performing topographic and geodetic work, constructing geodetic networks, GNSS observations, photogrammetric processing, and creating digital models of relief. These documents regulate measurement accuracy, error control methods, standardised approaches to office processing and the formation of source materials. Since modern geoinformation systems are based on digital data sets that must meet high accuracy requirements, regulatory methodologies remain a key factor in ensuring the quality of the digital infrastructure of territories [52].

In the context of urban planning, geospatial data is regulated by additional regulations that define the requirements for the creation, updating and use of urban planning documentation, in particular master plans, detailed plans of territories and zoning plans. These documents must contain standardised spatial layers focused on cadastral boundaries, transport networks, engineering infrastructure and functional planning zones. The requirements for their structure and formats are increasingly approaching the European standards LADM and INSPIRE Land Use Theme, which creates the conditions for the integration of urban planning documentation into digital analytical complexes [53].

Harmonisation of local data sets with national and international standards plays a decisive role in the development of municipal geoinformation systems. In particular, there is a need to standardise object catalogues, classification systems and attribute structures used in various areas of urban management. Different classification sets are used in zoning, engineering network modelling, green space inventory, traffic flow analysis and environmental parameter monitoring, which complicates the integration of these data into a single geoinformation platform. Research confirms that the implementation of a unified classification system, for example based on the INSPIRE Feature Catalogue, can significantly reduce data fragmentation and improve the quality of spatial interaction models [54].

An equally important area of regulatory support is metadata management, without which it is impossible to ensure the transparency and verifiability of the

processes of collecting, processing and publishing geospatial data. Metadata allows determining the origin of data, its spatial and accuracy characteristics, time limits, methods of collection and transformation, as well as restrictions on use. At the international level, metadata is regulated by ISO 19115, but in practice, the use of tools for automatic generation and updating of metadata integrated into GIS workflows is becoming increasingly important [55]. This is particularly relevant for large municipalities that operate hundreds of constantly updated geodata sets.

Modern approaches to digital governance, including the concepts of Smart City, Digital Twin and Urban Intelligence, rely heavily on geospatial data meeting regulatory requirements for accuracy, accessibility, openness and interoperability. Research confirms that it is standardised data sets that enable the construction of comprehensive models of urban processes, including transport flows, demographic dynamics, energy consumption and the state of the environment [56]. Ukrainian local communities implementing such approaches need a high-quality regulatory framework that will enable them to create objective spatial models for management decision-making.

In general, regulatory and standard support is a key element in the creation and operation of geoinformation systems of any scale. Its harmonisation with international standards and EU directives is one of the most important areas of development for the digital infrastructure of territorial communities in Ukraine. Without an adequate regulatory framework, it is impossible to implement modern models of intelligent data analysis, ensure the accuracy and reliability of spatial decisions, and form effective systems for monitoring and managing territories. Standardised geospatial data is the starting point for building analytical, predictive, and diagnostic models used in municipal management, urban planning, cadastre, transport systems, and environmental monitoring.

1.8   Geospatial data in the context of the Smart City concept

The Smart City concept has emerged as an integration platform for the development of urban systems, within which information technologies, digital services

and analytical tools are used to optimise management processes, improve the quality of life of the population and ensure sustainable development of territories. In the structure of a smart city, geospatial data plays the role of a system-forming resource, since most urban processes have a clearly defined spatial component — transport movements, construction, location of engineering networks, areas of environmental impact, territorial planning and infrastructure interaction. It is thanks to geodata that models of spatial analysis, forecasting of urban processes, optimisation of services and the formation of digital twins of the city are implemented [56].

Geospatial data in Smart City includes a wide range of sources, among which satellite imagery, remote sensing data, topographic and geodetic information, GNSS measurements, data from engineering networks, cadastral registers, sensor platforms, and information from urban IoT systems. They form multi-level spatial information bases that are used to analyse the state of territories, monitor critical infrastructure, model transport systems, assess safety levels, and plan urban development [57]. As a result, it is the quality, accessibility and standardisation of geodata that determines the effectiveness of smart city architecture and the applicability of artificial intelligence algorithms.

One of the fundamental components of a smart city is the creation of an integrated geoinformation platform that combines data from various urban management systems into a single digital environment. Such integration is made possible by the use of OGC protocols, standardised data models and service-oriented architecture, which allows local authorities to use aggregated spatial resources to model development scenarios, manage risks and optimise community resources [58]. Geospatial data in such a system becomes a structural element of the city's information core, ensuring the functioning of analytical panels, forecasting algorithms, and decision-making modules.

Modern Smart City platforms widely use data from sensor networks that record real-time indicators of atmospheric conditions, traffic, public transport congestion, noise levels, road surface conditions, engineering network parameters, and behavioural data of urban service users. This data is constantly integrated into the GIS environment, forming a dynamic spatial-temporal flow of information that requires specialised

algorithms for processing, filtering, and visualisation. The result is dynamic traffic maps, network congestion visualisations, environmental condition analytics, or interactive models of the state of urban infrastructure [59].

A special place in the Smart City structure is occupied by the concept of an Urban Digital Twin, which involves the creation of a comprehensive digital model of the territory that integrates spatial data, information flows from sensors, object behaviour models, and forecasting algorithms. The digital twin uses a multi-layered GIS in combination with machine learning methods, which makes it possible to model the impact of traffic flows, assess the condition of engineering systems, predict the development of construction, and analyse the risks of emergencies [60]. It is important that digital twins are becoming a practical tool for supporting management decision-making, allowing spatial dependencies to be identified, scenarios to be modelled, and the effectiveness of planning measures to be assessed.

In urban infrastructure management systems, geospatial data provides the ability to spatially and temporally assess the condition of objects, which is the basis for introducing the concept of 'infrastructure intelligence.' For example, in transport networks, the integration of GPS tracks, telematic data, road sensors and CCTV cameras allows the creation of subsystems for dynamic traffic light control, congestion forecasting and public transport route optimisation. Research confirms that it is the quality of geodata that determines the accuracy of such models and the speed of response of systems in real time. [61].

Geospatial data plays a decisive role in the formation of Smart City environmental modules. It is used to map pollution levels, assess green areas, model temperature anomalies, predict flood risks, and optimise the city's environmental policy. Combined with artificial intelligence methods, geodata allows hidden spatial structures to be identified, critical areas of environmental risk to be determined, and scenarios of climate change to be modelled at the level of urban agglomerations [62].

In the context of Smart City, it is important to integrate data on engineering networks — electricity, heat, water and gas supply — into a single geospatial infrastructure. The availability of complete and up-to-date data makes it possible to

model loads, predict failures, optimise repair work and improve the city's energy efficiency. Such models are particularly effective when they are integrated into the city's digital twin and supplemented with sensor measurements [63].

An important component of Smart City development is the regulatory framework for openness and interoperability of geodata. In European Union countries, the introduction of open spatial data formats (Open Data) has become a driving force for the development of community participation services, transparency in decision-making, and independent monitoring of the quality of urban services. Studies show that open geospatial data stimulates the development of local innovations, start-ups and analytical services that contribute to improving the functioning of urban space [64]. Ukrainian local communities that create open geoportals are moving closer to European models of smart governance based on openness and data unification.

In complex terms, geospatial data is the main information resource of the Smart City concept, ensuring the digitisation of urban infrastructure, the integration of services, the automation of monitoring and analysis processes, and the application of intelligent forecasting models. They form a platform for the development of modern urban management systems based on the principles of data accessibility, structure, semantic consistency, and scalability. At the same time, the effective use of geodata in a smart city depends on regulatory and legal support, the level of standardisation, the technological development of public services, and the ability to integrate data from different sources into a single GIS environment.

One of the key vectors for the development of Smart Cities is the formation of integrated urban mobility management systems that not only account for and monitor traffic flows, but also intelligently manage them based on geospatial analysis. Geodata allows the creation of 'urban mobility' models that cover private transport, bicycle infrastructure, pedestrian activity, public transport operations, and residents' behavioural patterns. Research confirms that the use of spatial models based on GPS tracks, transport network logs and mobile operator data increases the efficiency of street and road network planning and reduces the load on key transport corridors [65]. Combined with machine learning algorithms, such data allows predicting traffic jams, optimising traffic patterns,

and developing adaptive transport management systems.

An important feature of modern Smart Cities is the integration of geospatial data into urban security systems. Video analytics, noise sensors, social activity heat maps, and emergency response systems use spatially referenced information to identify potentially dangerous areas, analyse evacuation routes, and optimise the work of emergency services. Analytical models based on geodata reduce response times and increase the efficiency of police, fire, rescue and medical services [66]. In Ukraine, this component is particularly important given the need to monitor the security of territories and critical infrastructure and to respond quickly to threats in conditions of military and post-war risks.

Geospatial data plays a leading role in systems for monitoring the condition of engineering networks that ensure the functioning of critical urban facilities. Information about the location, depth, material, diameter of pipelines, technical condition and operating parameters is used to model accidents and predict repair needs. In modern Smart Cities, engineering system status models are based on the integration of geodata with data from sensor networks, including pressure and leak sensors in water supply networks, temperature sensors in heating networks, energy meters, IoT gas supply modules, etc. The use of artificial intelligence allows for the construction of predictive accident models, the identification of the most critical areas of infrastructure, and the optimisation of maintenance schedules [67].

The sector of urban land and real estate management is undergoing particularly dynamic development within the Smart City concept. Digital cadastral models and analytical tools based on geodata make it possible to assess the market value of properties, determine the efficiency of land use, forecast development trends, and model population density parameters. A number of countries have implemented systems for the automatic analysis of urban planning violations, which use remote sensing, LiDAR and neural network algorithms to automatically detect unauthorised construction, changes in land contours or non-compliance with functional zoning [68]. Such approaches can form the basis for the creation of real estate monitoring systems in Ukrainian communities that require transparent and objective assessment of development.

Among the latest trends in Smart City, the development of community participation systems (CivicTech) stands out, which use geospatial data to increase transparency and involve citizens in planning processes. Online maps of public appeals, interactive platforms for submitting proposals for changes in the city, crowdsourcing of environmental problems, maps of infrastructure damage or hazardous areas — all these tools are based on geospatial data. Studies show that such services significantly improve communication between the community and local authorities, while giving citizens a sense of involvement in the development of the city [69].

The comprehensive use of geospatial data in Smart Cities opens up the possibility of introducing intelligent resource management systems. For example, in the energy sector, geodata is used to determine the solar energy potential of individual buildings, model wind flows, create energy consumption maps, and forecast grid loads. The combination of remote sensing data, relief maps, 3D models and IoT measurements allows the creation of infrastructure indicators that enable effective planning of a city's energy efficiency [70].

In natural resource management systems, geospatial data enables the monitoring of green spaces, the assessment of ecosystem services, the identification of heat islands, the monitoring of changes in soil and vegetation cover, and the modelling of natural risks. The integration of Sentinel-2 satellite data, LiDAR, UAV imaging, and ground observations forms a powerful information resource for implementing nature-based solutions in cities [71].

Thus, geospatial data is the foundation for the functioning of a smart city, providing analytical, diagnostic, predictive, and infrastructural components of urban digital platforms. It supports the integration of departmental systems, the automation of management processes, the creation of digital twins, the development of citizen participation, and the formation of intelligent tools for monitoring and forecasting. The effective development of a smart city directly depends on the quality, relevance, completeness, and interoperability of geospatial data, as well as on the system's ability to ensure its secure, standardised, and open processing for a wide range of users and services.

2 METHODS OF PRELIMINARY PROCESSING OF GEODETIC AND GEOSPATIAL DATA

2.1 Theoretical foundations of preliminary processing of geodetic data

Preliminary processing of geodetic data is a fundamental stage of the geoinformation cycle, which determines the quality, reliability and analytical suitability of spatial information for further use in municipal geoinformation systems. In the context of modern territorial management, where decisions are made based on the integration of diverse sources of geodata and increasingly rely on automated and intelligent analysis methods, pre-processing ceases to be a purely technical procedure and acquires methodological significance. It is at this stage that the information quality of spatial models is formed, which subsequently determines the reliability of the results of spatial analysis and forecasting [15].

The theoretical basis for the preliminary processing of geodetic data is the provisions of measurement theory and error theory, which consider the process of obtaining coordinate and elevation characteristics as the result of a combination of random and systematic factors. Within this theory, geodetic measurements are interpreted as realizations of stochastic processes, which are characterized by the presence of noise, correlations between observations, and the dependence of the accuracy of results on the conditions of work performance. Accordingly, preliminary data processing is aimed at identifying, evaluating and minimising the impact of errors in order to obtain the most probable values of the measured parameters [72].

In the classical geodetic approach, preliminary processing includes checking the completeness and correctness of the initial observations, rejecting gross errors, applying statistical quality control criteria, and converting the measurement results to a single coordinate and elevation system. These procedures form the basis of office processing, which has historically been performed in a semi-automated mode with the active participation of a geodetic specialist. However, with the transition to digital GIS

and mass data sources, traditional methods of pre-processing need to be rethought and formalised, taking into account the volume and heterogeneity of modern geodata [73].

In the classical geodetic approach, preliminary processing includes checking the completeness and correctness of the initial observations, rejecting gross errors, applying statistical quality control criteria, and converting the measurement results to a single coordinate and elevation system. These procedures form the basis of office processing, which has historically been performed in a semi-automated mode with the active participation of a geodetic specialist. However, with the transition to digital GIS and mass data sources, traditional methods of pre-processing need to be rethought and formalised, taking into account the volume and heterogeneity of modern geodata [10].

An important theoretical aspect of preliminary processing of geodetic data is the concept of normalisation and unification of spatial information. In municipal GIS practice, geodetic data comes from various sources, collected in different years, using different methods and coordinate systems. Without bringing such data to a single spatial and semantic standard, it is impossible to combine and analyse it correctly. The theoretical basis for normalisation is based on the principles of geodetic transformations, the theory of cartographic projections, and spatial interoperability standards [74].

With the development of digital technologies and the Smart City concept, the pre-processing of geodetic data is taking on a new meaning related to the need to prepare data for automated and intelligent analysis. Machine learning and neural network modelling algorithms are sensitive to the statistical properties of input data, which necessitates formalised procedures for cleaning, scaling and structuring geodetic information. In this context, pre-processing is considered a key stage of the GeoAI pipeline, which determines the effectiveness of further model training and the reliability of predictive results (Fig. 2.1) [4].
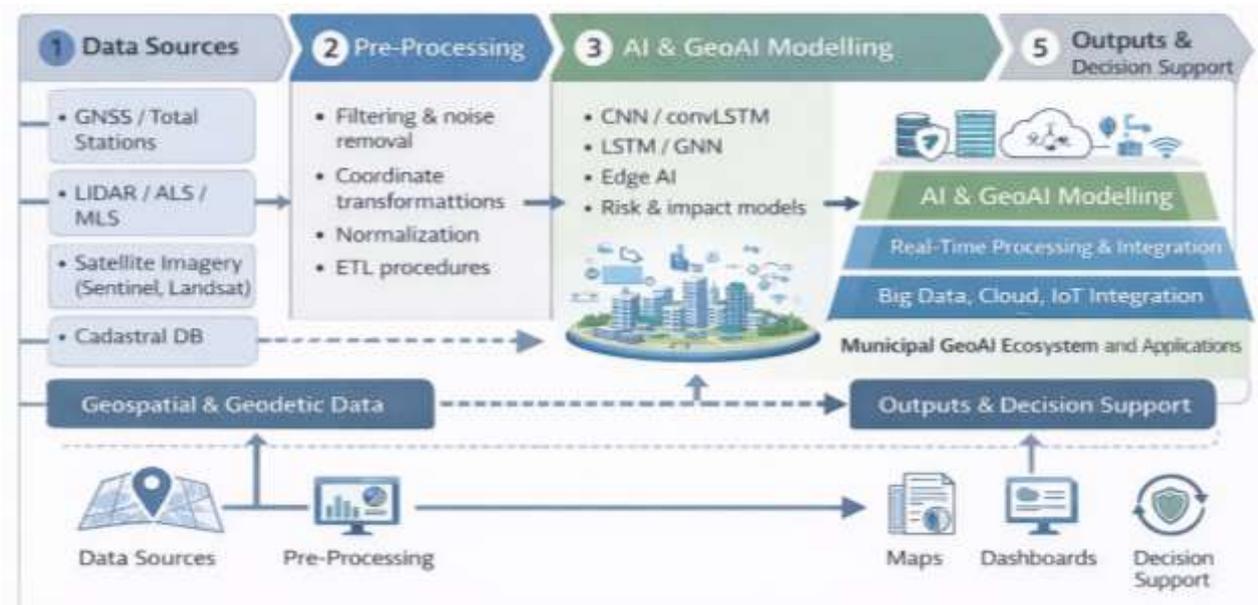
*Fig. 2.1 — Preliminary processing of geodetic data in the geoinformation and
intelligent conveyor of municipal GIS*

The theoretical foundations of preliminary processing of geodetic data are also closely related to the concept of geoinformation quality management. According to international standards, the quality of geodata should be assessed based on a set of indicators, including accuracy, completeness, logical consistency, and timeliness. Pre-processing is a tool for achieving these indicators, ensuring control and correction of data before it is used in analytical and management tasks [25].

Thus, the theoretical foundations of preliminary processing of geodetic data form the methodological basis for building modern municipal geoinformation systems focused on intelligent analysis and decision support. Recognising the role of this stage allows us to move from fragmented technical procedures to a systematic approach, in which pre-processing is considered an integral part of the geoinformation and management cycle. This creates the necessary prerequisites for a detailed consideration of specific methods of filtering, smoothing and normalising geodetic data, which is the subject of the next section.

2.2 Filtering, smoothing and normalisation of geodetic measurements

Filtering, smoothing and normalisation of geodetic measurements are key components of geodata pre-processing aimed at reducing the impact of random and systematic errors, increasing the stability of spatial models and ensuring the suitability of data for further analytical and intellectual processing. In the context of municipal geoinformation systems, these procedures are particularly important as the volume of geodetic information continues to grow and its sources become increasingly diverse, ranging from classic geodetic surveys to GNSS observations, laser scanning and sensor networks. Without the systematic application of filtering and smoothing methods, such data cannot be effectively used to support management decision-making [72].

The theoretical basis for filtering geodetic measurements is based on the principles of random process theory and mathematical statistics, where observations are considered as the sum of useful signals and noise. The main purpose of filtering is to separate the informative component of measurements from random fluctuations that have no physical meaning. In geodesy, filtering approaches are traditionally used to process time series of coordinates, elevation marks and angular measurements, in particular in GNSS observations and dynamic surveys. In municipal GIS, the results of such filtering are used to form stable spatial models necessary for analysing deformations, movements and changes in infrastructure objects (Fig. 2.2) [15].

One of the most common approaches to filtering geodetic data is the use of linear and nonlinear filters, among which moving average, exponential smoothing, and Kalman filter methods occupy a special place. The latter is widely used in GNSS data processing due to its ability to take into account both the statistical characteristics of noise and the dynamics of object movement. In the context of municipal geoinformation systems, the Kalman filter is used to smooth the trajectories of mobile objects, analyse changes in the coordinates of engineering structures, and monitor land deformations [75].

Smoothing of geodetic measurements is similar in meaning to filtering, but is more focused on reducing local data fluctuations and forming generalised spatial

trends. In geoinformation systems, smoothing is widely used in the construction of digital models of relief, surface and other continuous fields, where it is necessary to eliminate random irregularities caused by measurement noise. Smoothing methods such as spline approximation, local regression, and Gaussian smoothing improve the clarity and analytical value of spatial models, which is particularly important for spatial planning tasks (Fig. 2.2) [17].

Normalisation of geodetic data is a necessary step in preparing information for further analysis, especially when integrating heterogeneous sources. In theoretical terms, normalisation consists of bringing data to a single scale, units of measurement and statistical characteristics, which ensures their comparability and correct interpretation. In municipal GIS, normalisation is used when combining geodetic data of varying accuracy obtained at different times, as well as when preparing data for use in analytical and predictive models [10].
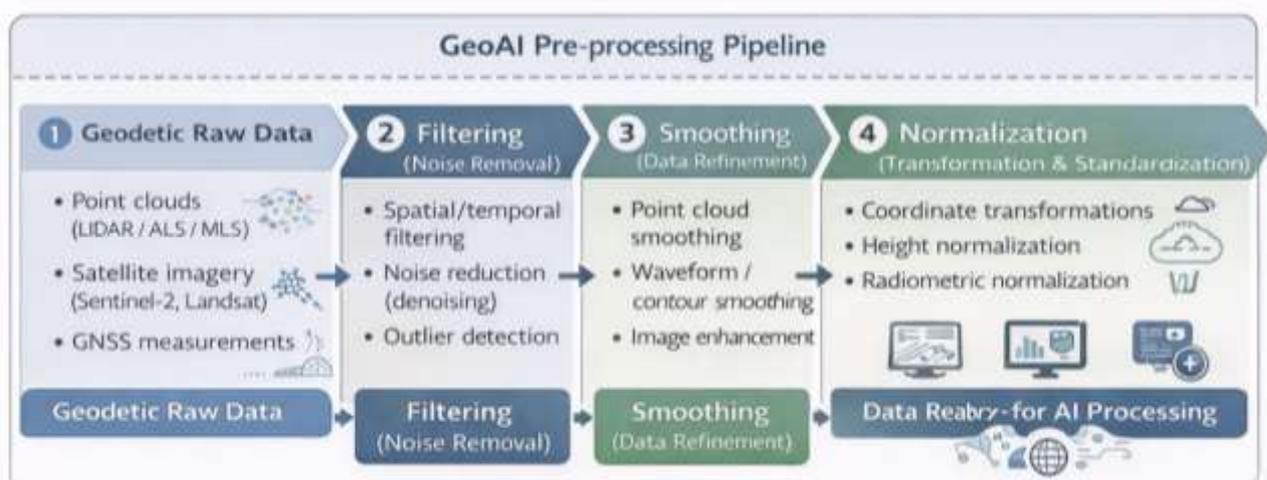
Fig. 2.2 — Filtering, smoothing and normalisation in the pre-processing of geodetic data

Normalisation is particularly important when applying machine learning and neural network modelling methods to geodetic data. Intelligent algorithms are sensitive to the ranges of input parameter values and statistical properties of data, which necessitates their preliminary scaling and standardisation. Without proper

normalisation, model training results may be unstable or distorted, which negatively affects the quality of forecasting and decision support in municipal GIS [4].

To summarise, it should be noted that filtering, smoothing and normalisation of geodetic measurements are interrelated elements of a single process of preliminary processing of geodata. Their comprehensive application ensures high quality spatial information, increases the reliability of spatial analysis results, and creates a solid foundation for the further use of intelligent methods in municipal geoinformation systems. This necessitates a detailed consideration of the procedures for identifying and eliminating anomalous values and topological errors, which is the subject of the following sub-clause.

2.3 Transformation of coordinate systems and conversion of data to a single spatial environment

The transformation of coordinate systems is one of the key stages of preliminary processing of geodetic data, without which it is impossible to form a coherent spatial environment for municipal geoinformation systems. In the practice of territorial management, geodetic and geospatial data come from different sources, created at different times and using different coordinate systems, geodetic datums and cartographic projections. In the absence of a unified spatial basis, such data cannot be correctly combined, which leads to spatial shifts, topological conflicts and erroneous analysis results. That is why coordinate transformation is considered not as an auxiliary technical operation, but as a methodologically important stage in the formation of a community's geoinformation space. [76].

In theoretical terms, the transformation of coordinate systems is based on the principles of higher-level geodesy, in particular on the theory of geodetic datums, ellipsoids of rotation and spatial transformations. A geodetic datum defines the position of an ellipsoid relative to the Earth's body and serves as the basis for calculating the coordinates of points on the Earth's surface. Different coordinate systems may differ in terms of ellipsoid parameters, orientation and implementation on the ground, which

necessitates the use of mathematically sound transformation models for transition between them [77].

In geographic information systems, the most common transformations are linear and affine transformations, as well as spatial transformations such as Gelmert transformations, which use three, seven, or more parameters. The choice of a specific transformation model depends on the nature of the source data, the scale of the territory, and the accuracy requirements. In municipal GIS, where spatial analysis is often performed at the level of individual neighbourhoods and land plots, even minor transformation errors can have significant consequences for management decisions. Therefore, the application of transformations must be accompanied by accuracy assessment and residual error control (Fig. 2.3). [73].
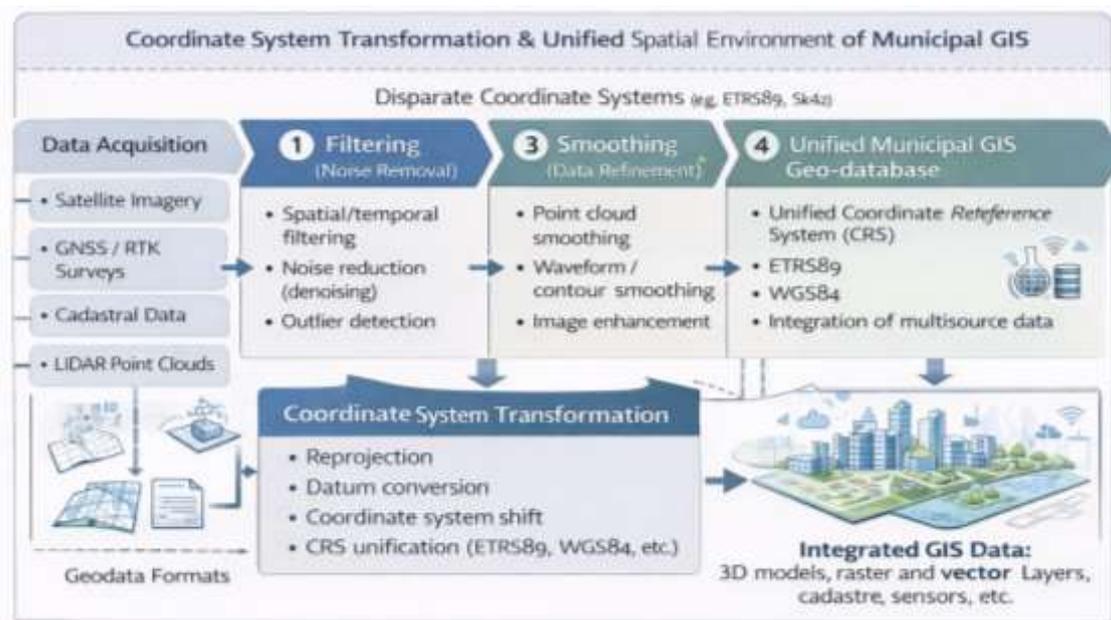
Fig. 2.3 — The process of transforming coordinate systems and forming a unified spatial environment for municipal GIS

A particular challenge in municipal geographic information systems is bringing historical geodetic materials, cadastral plans, and modern digital data into a unified spatial environment. Such materials were often created in local or outdated coordinate systems, making it impossible to use them directly without prior transformation. In this case, coordinate transformation is combined with geometric alignment procedures,

refinement of transition parameters and verification of control point conformity, which ensures the integration of data from different time periods into a single geoinformation model of the territory [76].

An important aspect of coordinate system transformation is the harmonisation of geodetic data with global and regional positioning systems. The use of satellite technologies, in particular GNSS, is based on global coordinate systems such as WGS 84, which do not always correspond directly to national or local systems. In municipal GIS, this necessitates a correct transition between global and local coordinate systems, taking into account geodetic parameters and regional characteristics, which is critical for ensuring the accuracy of engineering and cadastral work [72].

Bringing geodetic data into a single spatial environment in municipal GIS goes beyond mere coordinate transformations and includes the harmonisation of projections, units of measurement, scales and topological rules. The formation of a unified spatial environment means the creation of a coordinated geoinformation base in which all spatial objects are correctly correlated with each other and can be used for comprehensive analysis and modelling. This approach ensures the integrity of geospatial data and is a prerequisite for the further application of intelligent analysis methods [10].

To summarise, it can be argued that the transformation of coordinate systems and the conversion of geodetic data into a single spatial environment is a necessary prerequisite for the formation of integrated municipal geoinformation systems. The quality of this stage determines the correctness of the integration of heterogeneous data, the reliability of spatial analysis results, and the effectiveness of management decisions. This justifies the need for further consideration of quality control and validation procedures for prepared geodata, which is the subject of the next sub-section.

2.4   Office processing of geodetic data in GIS and CAD

Office processing of geodetic data is the final stage of spatial information preparation after field measurements and preliminary digital processing and plays a

key role in forming a high-quality geoinformation basis for further analysis, modelling, and management decision-making. In modern conditions, office processing is increasingly integrated with geographic information systems (GIS) and computer-aided design (CAD) systems, allowing a transition from traditional isolated procedures to a unified digital environment for processing, analysing and visualising geodata. In municipal geoinformation systems, this stage is of particular importance, as it ensures the coordination of metric accuracy, logical structure and visual representation of spatial data (fig. 2.4) [15].
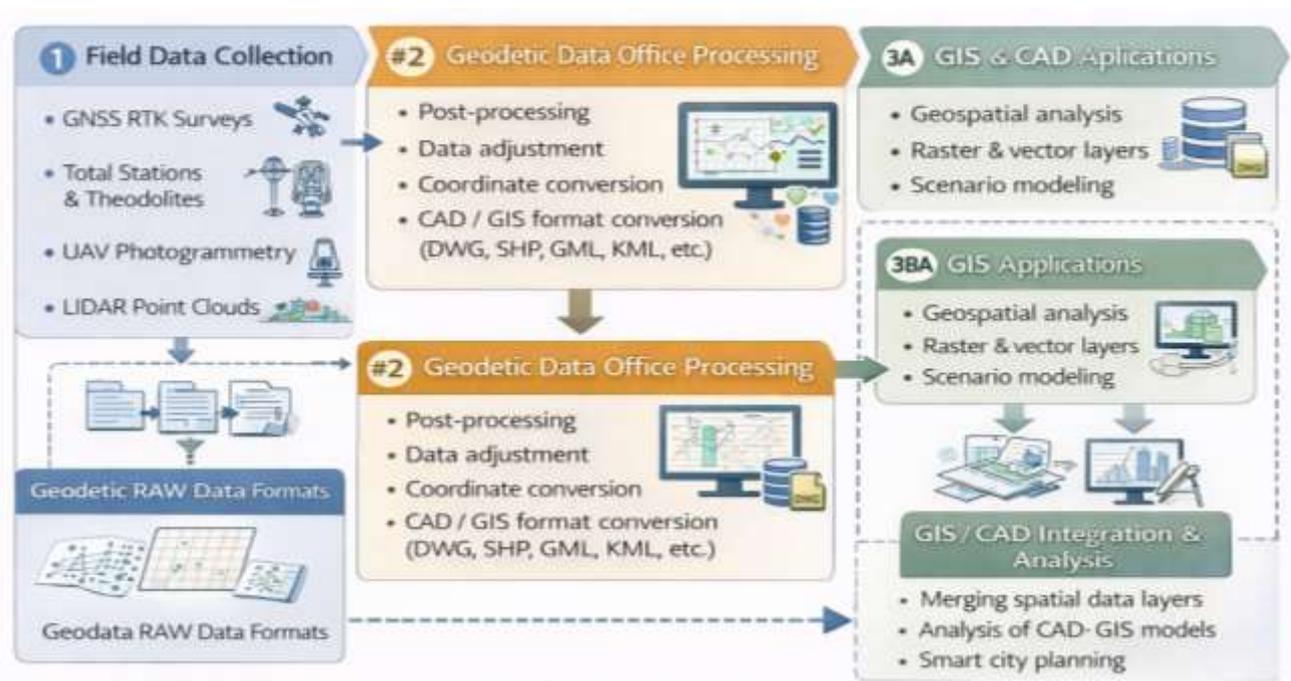
Fig. 2.4 — The place of geodetic data processing in the interaction between GIS and CAD in municipal geoinformation systems

In the classical sense, office processing includes checking measurement results, calculating coordinates and elevations, constructing a planimetric and altimetric base, and creating cartographic and topographic materials. However, with the development of digital technologies, these procedures have undergone significant transformations. Office processing is no longer limited to computational operations, but includes a set of actions aimed at creating structured digital geodata sets suitable for integration into a GIS environment and use in analytical and predictive models. It is at this stage that

the transition from 'raw' geodetic measurements to full-fledged spatial objects with clearly defined geometry and attribute content takes place [73].

Geographic information systems perform integration and analytical functions in the process of office processing. They ensure the storage of geodetic data in the form of spatial layers, support work with topological relations, and enable spatial quality control. In a GIS environment, office processing includes editing the geometry of objects, checking their spatial consistency, eliminating overlaps and gaps, and forming attribute tables that reflect the semantic characteristics of objects. Such operations are necessary to ensure the correctness of further spatial analysis and modelling [10].

Computer-aided design systems play a different but equally important role in the office processing of geodetic data. CAD systems are traditionally focused on accurate geometric modelling and the preparation of engineering documentation, which makes them indispensable for the creation of topographic plans, working drawings and design solutions. In the context of office processing, CAD systems ensure high metric accuracy in the construction of objects, support for complex geometry, and compliance of graphic materials with current regulations and standards. At the same time, the limited analytical capabilities of CAD systems necessitate their close integration with the GIS environment [78].

The integration of GIS and CAD in the process of office processing of geodetic data allows combining the advantages of both approaches — the accuracy and formalisation of engineering design with the analytical and management capabilities of geographic information systems. In municipal GIS, such integration provides a unified digital space in which geodetic data is used both for creating technical documentation and for spatial analysis of territorial development. This is especially important when preparing urban planning documentation, managing engineering infrastructure, and planning territorial development [76].

Current trends in the development of geodetic data processing are related to the automation of routine operations and the introduction of intelligent processing algorithms. Scripting and modelling approaches are increasingly being used in GIS environments to automate the processes of editing, checking and reconciling geodata.

This creates the conditions for a transition from manual office processing to semi-automated and automated work processes, which is critically important in the context of large data volumes and high demands on the speed of management decisions [8].

In summary, the office processing of geodetic data in GIS and CAD is a multi-component process that combines computational, graphical, analytical and informational aspects. The quality of this stage determines not only the accuracy of spatial models, but also the possibility of further application of intelligent analysis methods and neural network modelling. That is why office processing is considered a critical stage in preparing geodata for use in modern municipal geoinformation systems, which logically justifies the transition to considering intelligent approaches to the automation of geodetic processes in the next section of the monograph.

2.5 Preparation of geodetic data for intelligent analysis and machine learning

The preparation of geodetic data for intelligent analysis and machine learning is a system-forming stage of modern geoinformation research, since it is at this level that a fundamental transition takes place from classical methods of geodetic and office processing to the use of artificial intelligence algorithms as tools for identifying patterns, forecasting and supporting management decisions. This stage is particularly important in municipal geoinformation systems, as geodetic data serves as the basic spatial foundation for analysing territorial development, managing infrastructure and monitoring changes in the urban environment. At the same time, machine learning algorithms do not work directly with geometric objects in their traditional geoinformation representation, which necessitates a profound transformation of geodetic information into a form suitable for intellectual processing [4].

In theory, preparing geodetic data for machine learning is based on integrating geodesy, geoinformatics, mathematical statistics, and data learning theory. Geodetic measurements, which reflect real space in the form of coordinates, heights, directions, and distances, are used in classical GIS primarily to construct accurate spatial models.

In machine learning, however, these data are treated as multidimensional numerical arrays in which not only the absolute values of the parameters are important, but also statistical dependencies, correlations, and latent structures. Thus, the preparation of geodetic data involves not only technical conversion of formats, but also a conceptual change in the way they are interpreted (Fig. 2.5) [8].
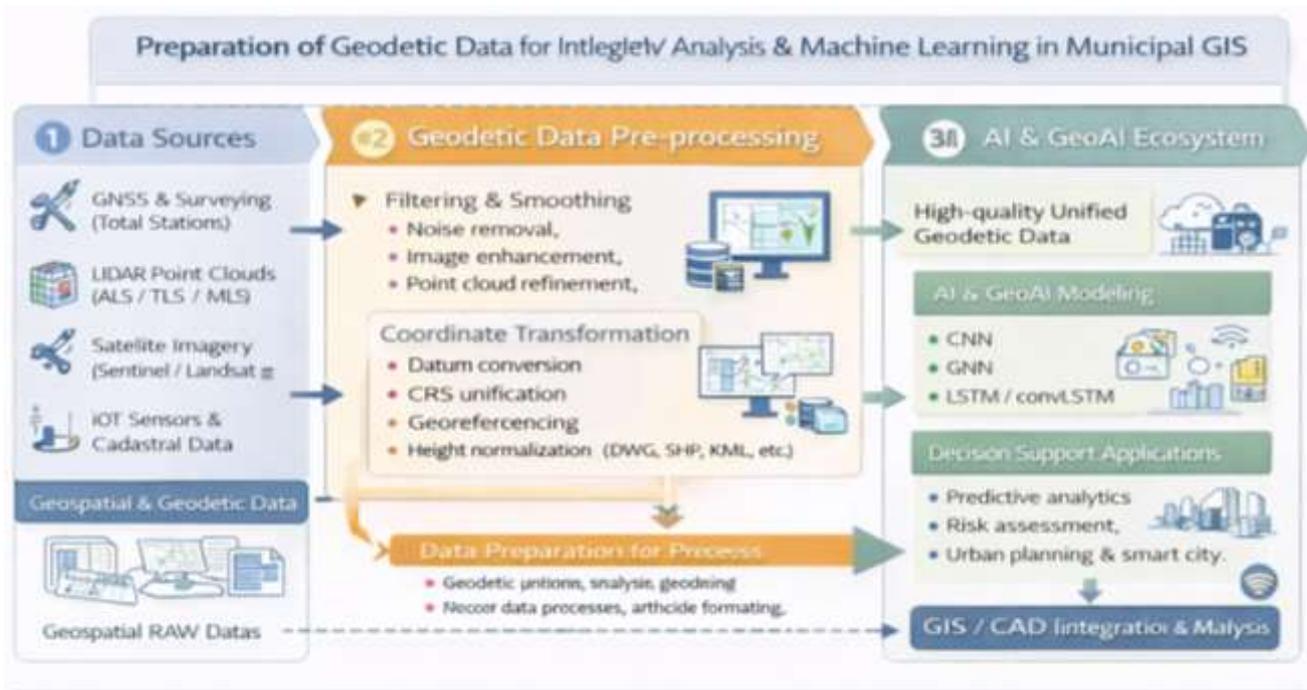
Fig. 2.5 — Conceptual model for preparing geodetic data for intelligent analysis and machine learning in municipal GIS

One of the key aspects of preparing geodetic data is the formation of a feature space that adequately reflects the spatial organisation of the territory. Geodetic objects in municipal GIS are characterised by complex multidimensionality, including geometric parameters, spatial relationships, temporal variability, and contextual environmental factors. The data preparation process involves selecting relevant characteristics, constructing derived features, and eliminating parameters that do not carry analytical weight. Such transformation is particularly important for territorial development analysis tasks, where patterns are nonlinear and multifactorial in nature [79].

A significant problem in the preparation of geodetic data is the presence of gaps, anomalous values, and noise, which are typical for spatial datasets formed in real conditions. Gaps may arise due to incomplete coverage of the territory with surveys, different data update frequencies, or technical limitations when collecting information. Anomalous values are often the result of measurement errors, coordinate system transformation errors, or incorrect integration of different geodata sources. For machine learning algorithms, such defects can lead to significant distortion of the learning process, requiring the use of specialised methods of data cleaning, interpolation, and statistical correction [80].

When preparing geodetic data, special attention should be paid to scaling and standardising features. Geodetic parameters can vary in value ranges and units of measurement by several orders of magnitude, which complicates the use of many machine learning algorithms. Without bringing the data to a single scale, the process of optimising model parameters becomes unstable, and the results become sensitive to the dominance of individual features. Standardisation and normalisation of data ensure the correct operation of neural networks, increase the convergence speed of algorithms, and improve the interpretability of modelling results [79].

A fundamentally important feature of geodetic data is the presence of spatial autocorrelation, which manifests itself in the statistical dependence of parameter values in spatially close objects. Ignoring this effect when preparing data for machine learning can lead to an overestimation of model accuracy and false conclusions about their predictive capabilities. Therefore, modern GeoAI approaches involve the formation of training samples taking into account the spatial structure of data, multi-scale interrelationships, and territorial context. This ensures the generalisability of models and their correct application in real municipal management conditions [81].

In municipal geoinformation systems, the preparation of geodetic data for intelligent analysis is complicated by the need to integrate information resources from different times and scales. Geodetic surveys, cadastral data, remote sensing materials, and sensor observation results form a heterogeneous spatio-temporal array in which each type of data has its own characteristics of accuracy, relevance, and reliability.

Preparing such data for machine learning involves not only technical unification of formats, but also conceptual harmonisation aimed at forming a unified information image of the territory suitable for intelligent analysis [2].

The final stage in preparing geodetic data for machine learning is the formation of training, validation and test sets that ensure an objective assessment of the quality of intelligent models. In a geoinformation context, this process must take into account the spatial integrity of the data and prevent so-called spatial information leakage, when objects with close spatial locations fall into different samples. Proper data organisation at this stage is a prerequisite for building models that can be generalised and used in practice in the management tasks of local communities.

Thus, the preparation of geodetic data for intelligent analysis and machine learning is a multi-level and conceptually rich process that combines geodetic, geoinformation and intelligent approaches. It provides a methodological transition from classical office processing procedures to the use of artificial intelligence as a tool for analysis, forecasting and support for management decision-making in municipal geoinformation systems. This creates a logical basis for further consideration of artificial intelligence and neural network modelling methods, which is the subject of the next section of the monograph.

2.6   Methodological readiness of geodetic data for intelligent modelling in municipal GIS

Summarising the results of the consideration of the processes of pre-processing, transformation, desk processing and preparation of geodetic data for machine learning, it is appropriate to formulate the concept of methodological readiness of geodata for intelligent modelling. In the context of municipal geographic information systems, this concept goes beyond the technical correctness of data and covers a set of conditions under which geodetic information can be used as a full-fledged basis for the application of artificial intelligence, neural network analysis and spatial forecasting methods.

Methodological readiness of geodata means that it is not only accurate and consistent, but also structurally, statistically and semantically adapted to intelligent processing.

In modern municipal GIS, geodetic data form the basic spatial framework onto which socio-economic, environmental and infrastructure layers are superimposed. However, without proper methodological preparation, this framework remains a passive carrier of information, suitable only for visualisation and classical spatial analysis. Only after completing the full set of procedures discussed in the previous sections does geodetic data acquire the properties necessary for intellectual analysis, in particular homogeneity, scale consistency, statistical stability and interpretability. (fig. 2.6) [8].
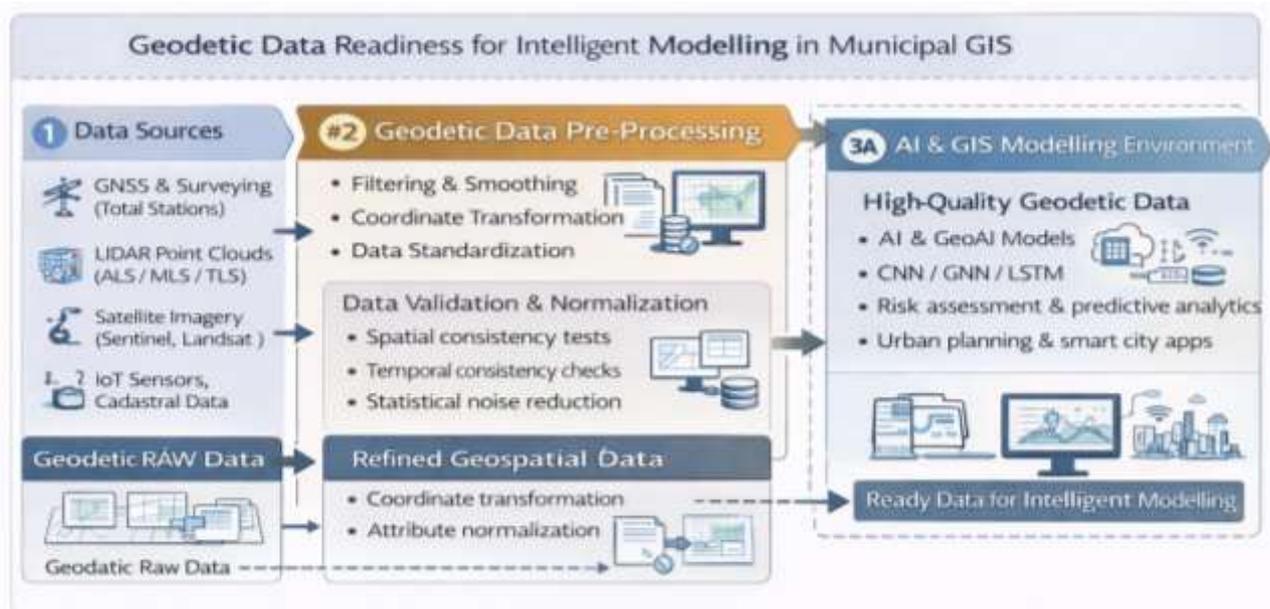
Fig. 2.6 — Methodological framework for the readiness of geodetic data for intelligent modelling in municipal geoinformation systems

The methodological readiness of geodetic data requires, first and foremost, an understanding that data quality in the context of artificial intelligence is multidimensional. In addition to the classic indicators of accuracy and completeness, characteristics such as statistical distribution of features, the presence or absence of autocorrelation, sample balance, and data stability over time become critically important. Machine learning algorithms are sensitive to the slightest distortions in the

data structure, so even minor methodological miscalculations at the preparation stage can lead to systematic errors in the modelling results [80].

In the context of municipal GIS, special attention should be paid to the spatial dimension of methodological data readiness. Geodetic information differs fundamentally from abstract tabular data sets in that each value has a clear spatial location and interacts with its surroundings. This means that the preparation of data for intelligent modelling must take into account the spatial structure of the territory, the hierarchy of objects, the multi-scale nature of processes and contextual dependencies. Ignoring these factors leads to the construction of models that demonstrate high formal accuracy but do not reflect the real patterns of spatial development [81].

The methodological readiness of geodetic data also requires their compatibility with the architecture of future intelligent models. Different approaches to artificial intelligence — from classical machine learning algorithms to deep neural networks — place different demands on the structure of input data. Therefore, geodata preparation should not be carried out in isolation, but should take into account the type of models that are planned to be used for analysis and forecasting. In this context, geodetic data is not only an object of processing, but also an active element in the design of an intelligent geoinformation system [4].

In the practice of territorial management, the methodological readiness of geodetic data has a direct impact on the quality of management decisions. Intelligent models built on incorrectly prepared geodata can generate erroneous recommendations for infrastructure development, land use, or risk management. On the other hand, a systematic approach to the preparation of geodetic data allows the creation of intelligent decision-making support tools that are capable of taking into account the complex spatial dynamics of territorial communities and providing scientifically sound forecasts of their development [2].

Thus, the methodological readiness of geodetic data for intelligent modelling is the result of a comprehensive and consistent process covering all stages of their processing — from initial measurements to the formation of training samples for machine learning. Therefore, the specified methodological basis is a necessary

prerequisite for moving on to the consideration of specific methods of artificial intelligence and neural network modelling, which is the subject of further research.

2.7   Methods of quality control, validation and accuracy management of geospatial data

Quality control of geospatial data is a key component of the process of their preliminary processing and preparation for use in municipal geoinformation systems. The quality of geodata determines the accuracy of further calculations, the reliability of spatial analysis models, the reliability of cartographic materials, the effectiveness of decision-making, and the possibility of integrating data from different sources into a single analytical environment. In modern GIS, quality control covers a wide range of procedures: from initial validation of GPS measurements to comprehensive assessment of data sets' compliance with international standards (ISO 19157, INSPIRE Data Quality), topological verification, statistical analysis, metadata analysis, and model reproducibility procedures.

Given the significant amount of geospatial information generated by modern sensors, geodetic instruments, mobile platforms, satellite systems, and unmanned complexes, quality control issues are becoming strategically important. Current research emphasises that it is the quality and structure of geodata that determine the applicability of intelligent algorithms and ensure the accuracy of further modelling of spatial processes [50].

The quality of geospatial data refers to a set of characteristics that determine the compliance of data with certain requirements for accuracy, completeness, consistency, relevance, logical correctness, and compatibility with external information sets. The international standard governing the concepts and criteria for quality assessment is ISO 19157:2013 'Geographic Information — Data Quality', which defines the following components:

- spatial accuracy;

- temporal accuracy;

- thematic accuracy;

- completeness;

- logical consistency;

- quality metadata.

INSPIRE also defines standardised quality requirements for spatial data sets, setting accuracy thresholds for different types of information, including cadastral boundaries, topographic features, transport networks, water bodies, infrastructure and planning restrictions. [49].

Spatial accuracy determines the degree of deviation of object coordinates from their true position. The following methods are used to assess spatial accuracy:

1. RMS-error. Used during coordinate transformations, georeferencing of images, and control of GNSS measurement accuracy.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{n}}$$

RMSE is the main criterion for:

- georeferencing rasters,

- comparing geodetic survey results,

- validating DEM/DSM,

- controlling UAV/LiDAR data.

2. Statistical evaluation of systematic and random errors. Used to analyse measurement stability, verify regression models, and identify trends in data.

3. Repeat measurement method. Involves repeat GNSS positioning or tacheometric measurements to determine coordinate stability.

4. Control by control points (GCPs, CPs). A common approach in remote sensing and UAV photogrammetry. GCPs provide absolute accuracy, while CPs provide independent validation.

The use of a GCP network is a key factor in the high accuracy of digital terrain models [82].

Logical consistency determines the compliance of the data structure with logical rules and topological dependencies. Topological errors can lead to serious inaccuracies in spatial analysis, for example:

- lack of common boundaries between polygons;
- self-intersections;
- "gaps" between cadastral plots;
- duplicates;
- incorrect node order;
- intersections of power lines or water pipes;
- breaks in the transport network;

Key methods of topological validation include:

- dissolve, cleaning, snapping;
- checking adjacency and connectivity rules;
- detection of topological gaps and overlaps;
- checking cycles in networks;
- geometric correctness analytics.

Topological rules are implemented in all modern GIS, especially in ArcGIS Data Reviewer, QGIS Topology Checker, GRASS GIS v.clean.

In urban planning and municipal GIS, the accuracy of data in the time domain is critically important.

The main methods of temporal quality control are:

- analysis of geodata collection dates;
- comparison of retrospective images with current data;
- temporal validation of sensor networks;
- control of data asynchrony from different sources;
- analysis of update frequency.

Modern approaches are based on the use of time-enabled layers, which allow dynamic datasets to be integrated into coherent temporal models [45].

Assessing DEM accuracy is important because terrain errors have a large-scale impact on watershed models, hydrology, snow models, transportation analysis, visibility modeling, and other applications [83].

Municipal GIS combines data from:

- GNSS;

- Total stations;

- UAVs;

- LiDAR;

- Satellite platforms;

- Engineering networks;

- IoT sensor devices;

- Cadastral registers;

Integration issues:

-   different coordinate systems;

-   different accuracies;

-   different semantic models;

-   lack of standardized attributes;

-   different time slices;

Modern approaches involve the use of:

-   a common geodetic basis;

-   a unified attribute structure;

-   spatial normalization;

-   statistical equalization models;

-   thorough validation after integration.

Research confirms that high-quality integration is a key condition for the correct operation of machine learning models [51].

Metadata contains information about: collection method, accuracy, date of capture, sensor parameters, usage restrictions, transformations, responsible persons, calculation algorithms.

Modern approaches automate metadata creation using semantic models and NLP algorithms [55].

The quality of geodata directly affects the performance of neural network models.

The main methods are: cross-validation, feature correlation analysis, selection of relevant features for anomaly detection, class balancing in classification tasks, and ground truth consistency checks.

Low-quality data causes model drift and concept drift — a shift in predictions over time, which has been confirmed by many studies [54].

Therefore, systematic quality control of geospatial data is a fundamental prerequisite for the development of municipal GIS, intelligent analysis systems, and digital twins of territories. High-quality data ensures:

- the reliability of spatial models

- the correctness of machine learning

- the interoperability of datasets

- stability of analytical solutions

- efficiency of territory management

Validation and accuracy control methods — from RMS analysis to topological verification, from ISO standards to ETL processes — are at the core of modern geoinformation analytics in local government management systems.

2.8   Integration of geospatial data from different sources

The integration of geospatial data from different sources is one of the most important stages of pre-processing, as it ensures the comprehensiveness, structural integrity, and analytical consistency of the information entering municipal geoinformation systems. The modern urban environment generates a huge array of data, which is formed from a wide range of technological platforms: GNSS measurements, tacheometric observations, UAV photogrammetry, laser scanning, satellite imagery, mobile sensors, IoT networks, and ground service data. Each of these

sources has its own metric characteristics, error model, different coordinate systems, different storage formats, and methods of semantic description of objects. That is why the integration process is not limited to the technical procedure of merging files, but is a complex set of mathematical, geodetic, topological, and information operations aimed at bringing all datasets into a single spatial and semantic environment. Studies emphasize that proper integration of geodata is a critical prerequisite for the application of artificial intelligence and spatial-analytical modeling methods, since inconsistent data can create systematic model distortions, cause errors in forecasts, and reduce the reliability of management decisions [51].

Integration is based on the preliminary conversion of data to a single coordinate system, which ensures spatial unification and avoids shifts caused by the use of different geodetic datums, projections, or local networks. In particular, GNSS data is in most cases generated in the global WGS84 or ITRF systems, while total station observations can be performed in local networks, and UAV data is tied to measured GCP points. LiDAR surveying uses its own geodetic basis, oriented towards IMU solutions and GNSS trajectories, while satellite platforms generate images in systems specific to their manufacturers. Therefore, the integration procedure involves solving the spatial transformation problem using Helmert models, as well as more complex polynomial and affine transformations that allow for local deformations, which are especially important for old topographic materials or networks that have undergone years of distortion.

A separate challenge is the varying accuracy of the data. For example, GNSS static observations provide millimeter-level accuracy, while tacheometric measurements have high local accuracy but do not provide absolute spatial reference without the use of GNSS. UAV data obtained using photogrammetry can have horizontal errors of 3–10 cm and vertical errors of up to 20 cm, depending on the number and location of GCPs. LiDAR provides the most accurate elevation values, but its spatial alignment depends on the quality of navigation sensors, in particular IMU. Satellite images have wide spatial coverage, but their accuracy ranges from 0.3 m (WorldView-3) to 10–30 m (Sentinel-2). For correct integration, it is necessary to apply

weighting coefficients that determine the contribution of each source to the final model. This approach allows less accurate sources to be "suppressed" when creating generalized surfaces, such as DEM, or when forming three-dimensional models of a city that include buildings, terrain, utilities, and green spaces. According to the researchers, weight alignment is critical for integrating photogrammetry and LiDAR data: correctly determining the weight ratio allows for the creation of optimized digital surface models that take into account the advantages of both technologies [82].

An equally important element of integration is the harmonization of data semantics, i.e., a uniform meaningful description of attributes. Different systems use their own object catalogs, different class designations, and different coding systems. For example, in cadastral data, the same objects may have different codes, in transport data, network models vary, and in environmental data, proprietary measurement scales are used. To eliminate these differences, semantic harmonization is used, which involves bringing all attributes into a single reference book. INSPIRE standards play a key role in this, as they regulate the content description of objects and provide a common data model for the entire spectrum of spatial themes [54].

The integration of GNSS and total station data is traditionally performed using joint observation adjustment procedures. GNSS provides an absolute spatial reference, while total station data refines the local geometry of the network. The use of the least squares method allows the optimal coordinates of network points to be determined, taking into account the weight characteristics of each type of observation. The integrated GNSS-total station network is the basis for all further work, including UAV photogrammetry, as it ensures the accuracy of GCPs and control points, which determine the quality of orthophotos and digital terrain models.

The integration of UAV photogrammetry and GNSS is also of fundamental importance, as the absolute accuracy of orthophotos and terrain models is determined by the accuracy of GCPs. In most cases, GNSS data is used to determine the coordinates of ground control points, which are set on the ground before the flight. During photogrammetric block alignment, GCP coordinates ensure correct scaling and orientation of the model, and control points allow independent validation of its

accuracy. Without GCP, the error of UAV DEM can increase by 3-6 times, which makes it completely impossible to integrate photogrammetry with other sources.

LiDAR is one of the most difficult sources to integrate because it forms a three-dimensional cloud environment that requires classification, filtering, and normalization. To integrate with other data, it is necessary to perform ground filtering, height normalization, and co-registration procedures, which allow you to reconcile elevation models and correctly match LiDAR points with DEM or DSM obtained from other sources. LiDAR is often used as a control source to verify the quality of photogrammetric models, as it has a significantly lower vertical error [83].

Satellite data is integrated with local sources through spatial alignment, resolution matching, and radiometric normalization. This is achieved through resampling, multi-resolution fusion, and data blending algorithms based on wavelet transform or principal component analysis. Satellite data often serves as a background layer for change analysis, land classification, anomaly detection, or integrated environmental modeling. [46].

The integration of data from IoT sensor networks with GIS is particularly important, as this data has a high level of noise, low coordinate accuracy, and a very high update frequency. To bring it into the GIS environment, GPS track filtering (Kalman, Savitzky–Golay), clustering, matching with the road network, and time normalization are used. IoT data allows the creation of dynamic traffic maps, traffic load models, and spatial scenarios of environmental parameters, but only after detailed integration processing.

Thus, the integration of data from various sources is a central process in the formation of a comprehensive geospatial environment that ensures the functioning of municipal GIS, digital twins of territories, monitoring systems, urban models, and intelligent algorithms. The universality of this process, its mathematical complexity, and the need to take into account accuracy characteristics make integration one of the most resource-intensive but at the same time key elements of modern geoinformation analytics.

2.9 Spatial-topological operations as a key element of geospatial data preprocessing

Spatial-topological operations are a fundamental part of the geospatial data preprocessing process, as they ensure the logical consistency, structural integrity, and formal correctness of spatial objects that are integrated into GIS. In any municipal geospatial environment, data from different services — land, engineering, transportation, environmental, demographic — come from different sources, are generated for different tasks, and often have significant geometric, structural, and semantic differences. Because of this, topological processing becomes not just desirable, but a prerequisite for further intellectual analysis, modeling, or the formation of spatial solutions. Leading research indicates that most errors in spatial modeling, particularly in network analysis, urban planning constraints, or cadastral analytics, arise not from measurement inaccuracies, but due to violations of object topology — line breaks, polygon overlaps, incorrect node order, distorted geometry, or lack of connectivity between objects that should be adjacent [50].

The topological structure of data determines the mutual location of objects and their spatial relationships: adjacency, connectivity, membership, hierarchical nesting, or intersection. Unlike purely geometric characteristics, topological dependencies are invariant with respect to transformations, scaling, or rotations, making them a fundamental characteristic for analytical and legally significant use of geodata. For example, a land parcel polygon cannot have self-intersections; the boundaries of adjacent parcels must coincide; engineering networks must form a continuous linear structure; roads must connect at nodes rather than form "hanging segments"; water bodies must follow the hydrological logic of the flow; and buildings cannot extend beyond cadastral plots or cross protected areas. If these rules are violated, any further analysis — from calculating flood zones to determining building density — will lead to false results.

The topological cleaning process usually begins with the identification of geometric defects, the most common of which are self-intersections, breaks, duplicate

vertices, "spikes," irregular polygons, incorrectly closed contours, or redundant points. These errors are recorded during the process of digitization, vectorization of satellite images, or integration of data from various sources. Geometric defects not only complicate further processing, but can also cause critical failures in buffer construction, overlap analysis, visibility zone creation, or neural network vectorization algorithms. Therefore, modern GIS provide tools for automated detection and correction of defects (QGIS Geometry Checker, ArcGIS Data Reviewer, GRASS v.clean), which allows for initial normalization of geometry before deeper topological verification.

After geometric normalization, topological dependencies are checked. In polygon-polygon topological models, it is extremely important to detect gaps and overlaps that arise between adjacent territories, especially when integrating cadastral data, functional zone boundaries, or land management documentation created at different times. The presence of a gap between two polygons means that part of the territory has no defined status, which is unacceptable for cadastral records. Overlapping polygons, on the contrary, create a situation of double counting or double assignment, which is particularly critical in urban planning and land and property relations. Topological tools allow you to automatically detect these problems and form corrective data sets that provide a strictly defined structure of territories.

A separate category of topological operations is formed by procedures for recomposing spatial objects — dissolving, aggregating, segmenting, and dividing geometry. They are used in tasks such as boundary normalization, harmonization of data of different scales, elimination of minor artifacts, creation of generalized models, or construction of thematic layers that require an orderly structure. Such operations are especially important in environmental monitoring, where various sources — multispectral images, LiDAR, UAV — provide heterogeneous data that requires spatial coordination. Recomposition allows the formation of homogeneous thematic areas, which become the basis for the application of classification algorithms, cartographic generalization, and spatial-statistical methods.

In linear systems—transportation and engineering networks—the key element is ensuring connectivity, since any break in the network leads to incorrect route analysis,

the inability to perform network modeling (e.g., shortest path, service area, routing), and inevitable errors in modeling the use of communication systems. For transport models, the correct formation of intersections is particularly critical so that the system can interpret the road network as a connected structure. For engineering networks — water, electrical, and heating — the topology reflects the logic of the system: flow direction, connection to sources, presence of valves, chambers, or transformer nodes. Any error in the structure negatively affects the modeling of accidents, water consumption, load calculations, or shutdown areas. Studies emphasize that network topology violations are the main factor in errors in the modeling of critical urban infrastructure [61].

Topological processing is also important for terrain and surface models, as digital elevation models (DEM, DSM) must be structurally consistent with linear and planar objects: watersheds must correspond to the hydrographic network, buildings must not "sink" below the terrain, and roadways must transition smoothly between elements. The integration of LiDAR and photogrammetry requires mandatory elevation normalization and correction of gross anomalies. The presence of elevation "jumps" or local artifacts leads to erroneous hydrological models, incorrect determination of flooding zones, and errors in visibility modeling. Therefore, the topological combination of DEM with other layers is a basic process of data preparation for risk analysis and infrastructure resilience assessment. [83].

An equally important component of topological processing is the creation of structured models based on rules (rule-based topology), where a set of logical constraints is specified for each spatial layer, which are automatically checked in the GIS. Such rules allow you to control the placement of objects in accordance with legislative, engineering, or urban planning requirements. For example, in urban planning documentation, a building cannot partially extend beyond red lines or protected areas; power lines must pass through permitted corridors; connection points cannot exist without being linked to the network; sanitary protection zones must completely cover the relevant objects; and land plots cannot cross the boundaries of

other plots. Thus, topological rules become an instrument of regulatory and legal
control, ensuring not only the technical but also the legal correctness of geospatial data.

In summary, spatial-topological operations are a critically important stage of pre-
processing, without which it is impossible to ensure the integrity of geospatial data, its
integration from various sources, and its further application in complex systems of
analysis, forecasting, and territory management. Topological consistency forms the
basis for creating reliable digital twins, monitoring systems, intelligent models of urban
development, and management decisions based on reliable spatial patterns. This makes
topological data processing not only a technical tool, but also a central component in
the formation of high-quality municipal geoinformation infrastructure.

2.10   Automation of geospatial data preprocessing

Automation of geospatial data preprocessing is one of the key areas of
development of modern geoinformation technologies, as it allows to significantly
increase the efficiency of processing large amounts of information, minimize the
human factor, ensure the reproducibility of results, and integrate data processing into
more complex analytical or management systems. In the context of municipal GIS,
automation is particularly important because the urban environment generates
dynamic, multi-source, and heterogeneous data that requires regular updating,
normalization, and quality control before integration into analytical models or artificial
intelligence modules. That is why ETL processes, the use of scripting languages,
automation tools in ArcGIS and QGIS, and the implementation of cloud computing
capabilities are becoming an essential part of geodata preprocessing. Scientific
research emphasizes that the automation of workflows in a GIS environment
significantly reduces data processing time, increases the accuracy of results, and allows
the creation of scalable solutions suitable for continuous monitoring and analysis. [84].

The basis of modern automation in GIS is the ETL (Extract – Transform – Load)
approach, which involves extracting data from various sources, transforming it, and
loading it into a unified environment with the possibility of further analysis. In

municipal GIS, the sources of such data can be cadastral databases, satellite platforms, GNSS measurements, LiDAR scanning files, traffic sensors, air quality monitoring systems, data from utilities, and other information systems that store their own data sets in various formats and structures. ETL procedures ensure the conversion of this data into a standardized format, its validity, semantic consistency, and reduction to a single coordinate system. In many cities, ETL pipelines are used for daily updates of transportation models, environmental monitoring, infrastructure geo-analytics, and maintaining an address register. The high level of formalization of ETL processes makes them suitable for full automation, including regular scheduled runs, data quality checks, and automatic error notifications.

An important automation tool in ArcGIS environments is ModelBuilder, a graphical interface that allows you to create complex processing models using sequences of geoprocessing operations. ModelBuilder allows you to implement a wide range of procedures: from simple geometry cleaning to complex spatial transformation processes, vector-raster transformations, overlap analysis, surface formation, data classification, and data merging. One of the key features of ModelBuilder is the ability to create multi-level models with looping or conditional operators, which enables the creation of adaptive workflows that change their structure depending on the quality or type of input data. In addition, any ModelBuilder model can be exported to Python code, allowing you to extend functionality and integrate models into other software solutions, as well as perform calculations in the ArcGIS Server or ArcGIS Enterprise cloud environment [85].

In QGIS, a similar tool is Graphical Modeler, which allows you to build workflows using the Processing Toolbox tools. Graphical Modeler supports a wide range of operations – filtering, topological cleaning, geometry transformation, vector-raster transformations, interpolation, classification, and algorithms from the SAGA, GRASS, and GDAL libraries. An important advantage of QGIS is the openness of the platform, which allows you to combine Graphical Modeler models with Python scripts (PyQGIS), create plugins, and automate processes at the system module level. This

makes QGIS suitable not only for local tasks, but also for complex municipal projects that require complete reproduction of procedures and integration with external systems.

Python is central to modern automation of geodata preprocessing because it allows you to create scalable, flexible, and highly productive processes. The GeoPandas library is widely used for vector data processing, supporting indexing, spatial filters, overlay operations, topological checking, and integration with PostGIS. The Rasterio, rio-xarray, and rioxarray libraries are used to work with rasters, allowing georeferencing, CRS transformation, resampling, and complex raster analysis using Numpy and Dask arrays. Python-oriented pipelines, such as prefect, luigi, and apache airflow, are widely used to automate ETL processes, providing complex workflow execution, logging, parallelism, and status verification. The ability to integrate Python with third-party APIs (e.g., OpenStreetMap, SentinelHub, Google Earth Engine) extends processing automation far beyond traditional GIS, creating unified analytical systems for intelligent geodata processing [86].

Automation also covers methods for managing large volumes of data (Big GeoData) that cannot be processed with traditional desktop tools. Examples of such platforms — Google Earth Engine, CARTO BigQuery, Amazon Athena, Microsoft Planetary Computer — allow for pre-processing of rasters, classification, data normalization, and index calculation on a global scale. Cloud platforms enable parallel execution of ETL operations, the ability to create automated computing pipelines, connect external sources, and execute scripts in server environments. Studies show that the use of cloud automation significantly reduces the processing time for large-scale geodata sets, increasing productivity tenfold [46].

In general, the automation of geospatial data preprocessing forms a complete ecosystem in which software models, scripts, server platforms, and cloud tools are combined into a single structure, ensuring full repeatability, scalability, and long-term stability of geoinformation processes. This is a prerequisite for building digital twins of territories, monitoring systems, urban analysis, network models, environmental and risk indicators, as well as complex artificial intelligence-based systems that require highly coordinated and systematically updated data sets. Automated processes are

becoming an integral part of modern geoinformation infrastructure, providing a reliable and accurate basis for management decisions at the local community level.

In practical terms, the automation of pre-processing of geospatial data in municipal GIS is most often implemented through a combination of formalized ETL process algorithms, Python scripts, models in ModelBuilder and Graphical Modeler environments, and SQL scripts for spatial DBMS. The generalized logic of building such a pipeline can be presented in the form of pseudocode, which describes the sequence of actions from loading raw data to forming a standardized geodatabase. This algorithm can be implemented in any toolkit, but from a methodological point of view, it reflects the key steps of automated preprocessing (Fig. 2.7, Appendix A).
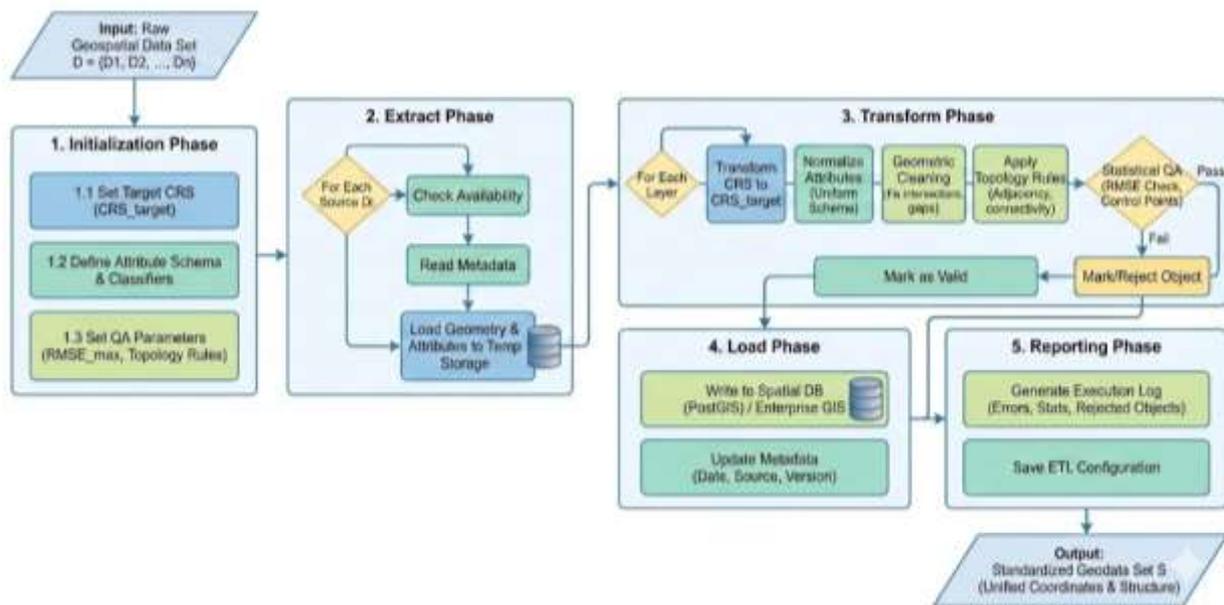
Fig 2.7 – Generalized diagram of the ETL process of preprocessing geospatial data for municipal GIS

In the context of implementing such an algorithm in Python, it is advisable to highlight separate scripts focused on typical tasks. For example, the basic script is for mass conversion of vector data, its geometric verification, and storage in a standardized format (GeoPackage or PostGIS). Such a script can act as the "core" of an automated conveyor that runs on a schedule or is integrated into more complex ETL scenarios (fig. 2.8, Appendix B.1).
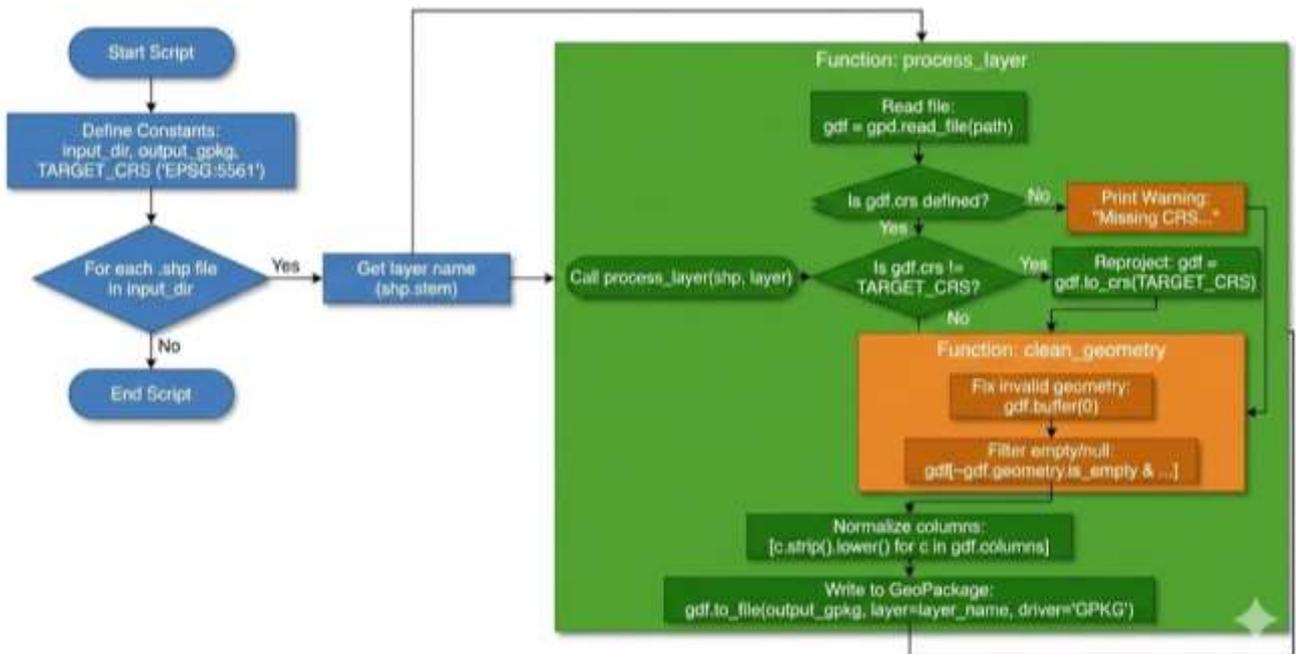
Fig 2.8 – An example of a Python script for automated conversion, cleaning, and saving of vector layers

The second typical class of tasks is the automated processing of raster data, in particular satellite images, their conversion to a single coordinate system, cropping outside the territorial community, calculation of indices (e.g., NDVI), and preparation for further classification. An example of such a script is a module that automates the creation of normalized indices and saves the results in a pre-processed data catalog (fig. 2.9, Appendix B.2).
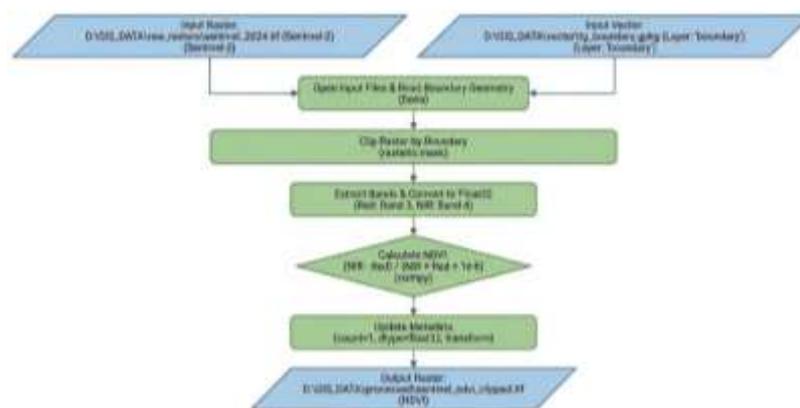
Fig 2.9 – – Example of a Python script for calculating NDVI and cropping rasters outside TG

For tasks where municipal data is stored in spatial DBMS (PostGIS), it is advisable to use SQL scripts as part of automated quality control and topological verification procedures. For example, regular validation of geometries and correction of invalid objects can be implemented directly at the database level (Fig. 2.10, Appendix C.1).
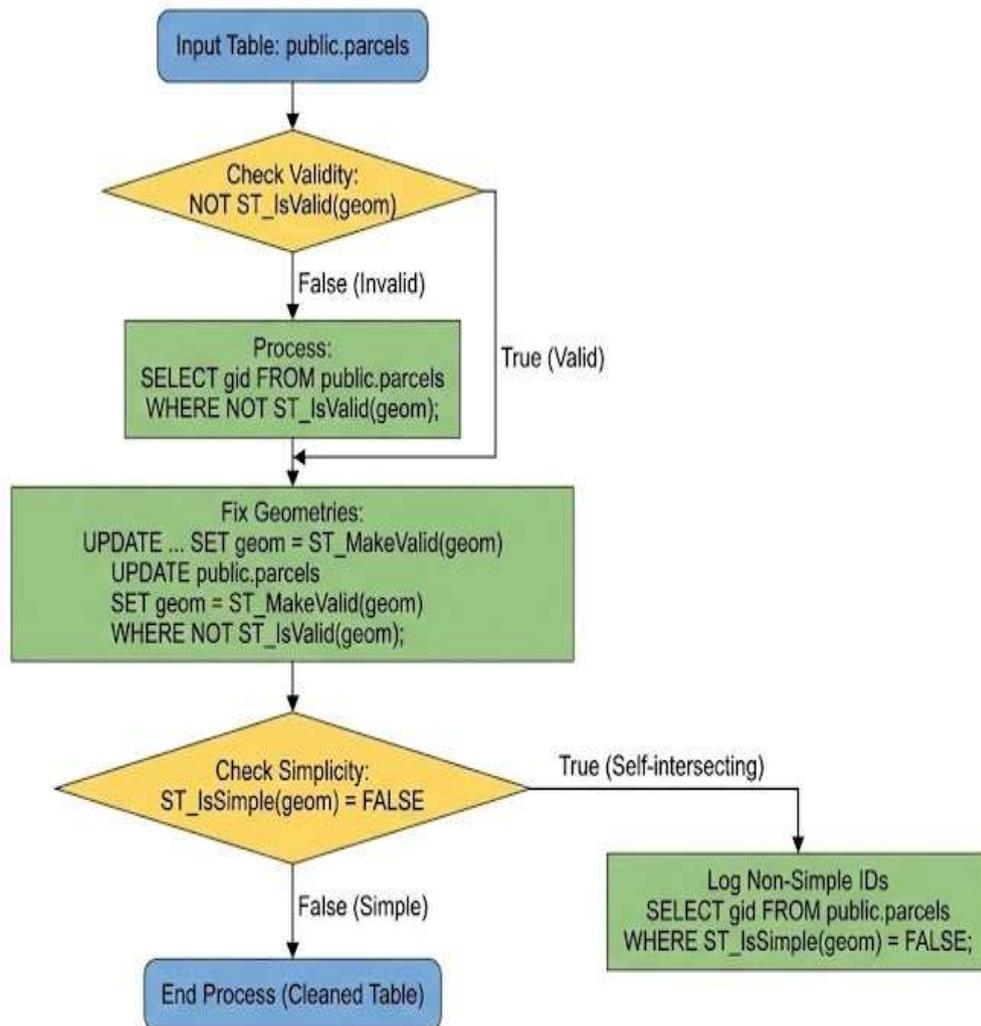
Fig 2.10 – Example of an SQL script for checking the validity and correcting geometries in PostGIS

Similarly, in the ArcGIS environment, a typical ModelBuilder model, exported to Python, can act as a template script for batch processing of datasets. It includes a sequence of geoprocessing tools – Project, Repair Geometry, Integrate, Feature Class To Feature Class – which form a formalized pipeline (Fig. 2.11, Appendix C.2).
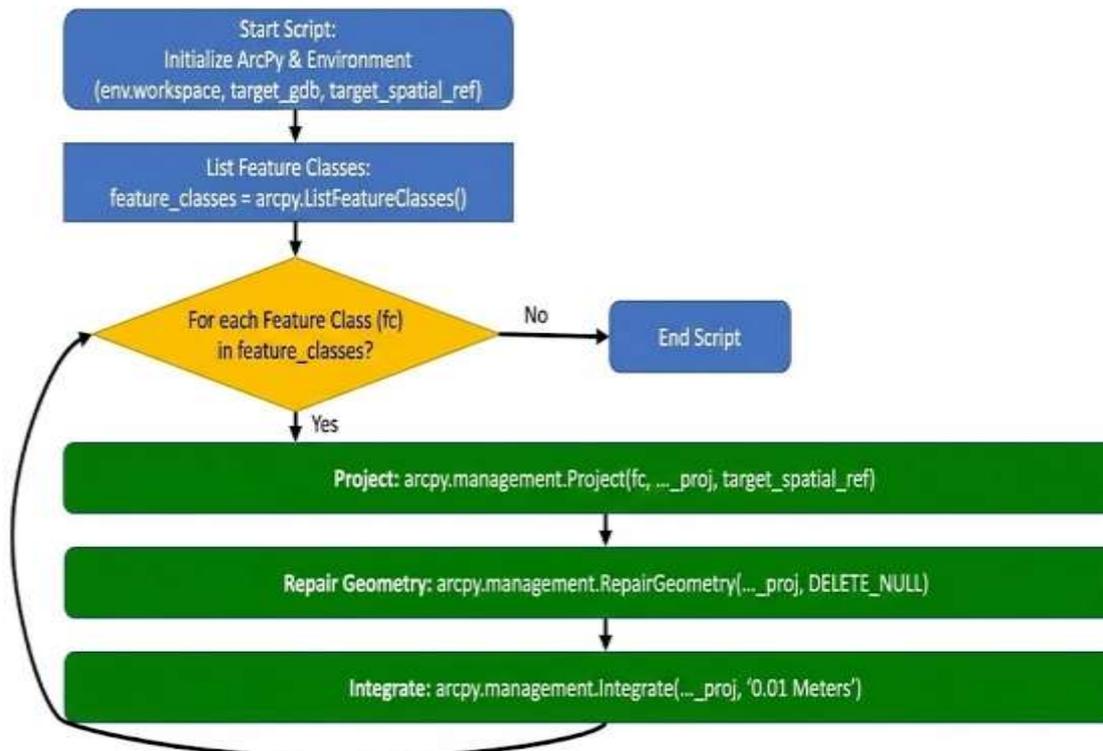
Fig 2.11 – Fragment of a Python script exported from ModelBuilder for batch conversion processing

It is important to note that the scripts and algorithms presented do not exist in isolation, but form a complete technological chain, within which each element is responsible for its part of the preliminary processing: coordinate system conversion, geometry cleaning, attribute normalization, clipping outside the territorial community, calculation of derived indicators (indices, surfaces), topology verification, and saving results in a standardized database. Their availability in the form of formalized "listings" and "algorithms" enables both machine and methodical reproduction of the process, which is important from the point of view of scientific verifiability and practical operation of municipal geoinformation systems.

2.11 High-performance processing of large geospatial data in municipal geographic information system

Modern municipal geographic information systems operate in an environment where data volumes are growing exponentially and the speed of information updates is

becoming a critical factor in the effective management of local communities. Geospatial data from Sentinel and Landsat satellite platforms, small-scale commercial satellites, LiDAR scanners, unmanned aerial vehicles, road sensors, IoT devices, transport systems, mobile operators, and city engineering services form multi-terabyte arrays that cannot be processed by traditional desktop geographic information systems. In such conditions, there is a need for high-performance computing approaches based on parallel processes, cloud services, distributed data storage, GPU acceleration, and specialized Big GeoData platforms. Research shows that the transition to high-performance processing methods can reduce the time spent on geospatial data analysis by a factor of ten [46].

The key characteristic of Big GeoData is not only its large volume, but also its structural complexity, temporal characteristics, the need for real-time processing, and integration with many types of sources. For such data, traditional ETL approaches, spatial queries, and analysis algorithms become insufficiently effective, since many operations—interpolation, classification, surface generation, segmentation, flow analysis, or predictive modeling—require significant computing resources. That is why municipal GIS practices use distributed computing environments that provide scalability and flexibility. One such environment is cloud analytics platforms, including Google Earth Engine, Amazon Athena, Microsoft Planetary Computer, SentinelHub, and CARTO BigQuery. Each of them has its own storage, digitization, and analysis tools, but they are all based on the use of parallel computing clusters, where analysis tasks are distributed among a large number of computing nodes.

Distributed data storage allows you to work with multi-terabyte arrays without having to download them locally. For example, Google Earth Engine provides direct access to satellite image archives covering a period of over 40 years and including entire planetary collections. Processing such volumes of data is possible thanks to the use of parallel computing models, where each satellite tile is processed by a separate cluster node. GEE's capabilities allow you to perform normalization, radiometric correction, NDVI, NDWI, NDBI index calculation, cloud cover analysis, noise filtering, territory classification, and segmentation directly in the cloud. Other

platforms, such as Microsoft Planetary Computer, provide similar functionality by combining satellite archives with machine learning tools, which also allows for real-time construction of environmental and urban models.

The use of GPU acceleration is another important aspect of high-performance geodata processing. Algorithms related to image processing, segmentation, neural network modeling, digital terrain modeling, 3D surface generation, or large raster analysis are extremely resource-intensive. GPU computing makes it possible to speed up processing by a factor of ten thanks to the parallel execution of operations on thousands of graphics cores. The cuSpatial, cuML, PyTorch, and TensorFlow libraries support GPU acceleration and enable the creation of complex models for classifying urban objects, detecting changes, or automatically vectorizing contours based on high-resolution satellite images. NVIDIA's developments, in particular the Earth-2 project, are aimed at creating climate models and digital twins of the planet based on deep neural network analysis of Big GeoData [127].

High-performance processing also includes distributed processing tools such as Dask, Apache Spark, and Ray, which allow you to work with large arrays of vector and raster data by distributing them across multiple computing nodes. These tools support the Cloud Optimized GeoTIFF (COG) format, which has become the standard for fast access to rasters in the cloud, as it allows data to be read in chunks without downloading the entire file. Vector data can also be processed in chunks using spatial indexing (QuadTree, R-Tree), which significantly speeds up overlay, clip, dissolve, and spatial join operations. This makes it possible to regularly update municipal datasets in near real time, for example, to automatically update building maps, analyze traffic, or identify areas of environmental discomfort.

In municipal practice, high-performance processing methods are often used for: regular analysis of large areas based on satellite archives; detection of illegal construction and changes in land use; monitoring of environmental indicators, including the state of vegetation, water resources, and thermal anomalies; processing LiDAR scans of cities with billions of points; building high-density digital terrain models; modeling traffic flows and pedestrian activity based on data from mobile

operators and IoT; analyzing damage, flooding, or other risks in crisis scenarios. Each of these processes requires the processing of large amounts of input data and regular model updates.

An important element of high-performance processing is automated data storage and optimization, in particular the use of cloud storage such as object storage (S3, Azure Blob, Google Cloud Storage), which supports parallel file reading and processing, as well as spatial formats oriented towards the cloud environment — COG, Zarr, Parquet, FlatGeobuf. The use of such formats allows the creation of optimized geodata processing pipelines, where each step — from normalization to classification — is performed in a distributed environment without the need for local data copying.

Thus, high-performance Big GeoData processing is a fundamental technological subsystem of municipal GIS, which provides the analytical capability of a city to work with large data sets, identify spatial patterns, form predictive models, and effectively manage infrastructure, the environmental situation, and territorial development. The combination of distributed computing, GPU acceleration, cloud archives of satellite images, and automated ETL conveyors forms the basis of modern digital urban solutions that ensure the accuracy, scalability, and high performance of spatial analyses.

An important direction in the development of high-performance geospatial data processing is the optimization of data structures and algorithmic procedures to ensure maximum efficiency when performing spatial operations on a city and regional scale. In this context, spatial indexes play a key role, providing efficient access to large vector and raster data sets without having to scan the entire file. Structures such as R-tree, QuadTree, KD-tree, and their distributed modifications are used in most high-performance databases — PostGIS, Spatialite, BigQuery GIS, CARTO, GeoMesa, GeoTrellis. Optimized indexes allow you to perform operations such as overlaying, clipping, determining intersections, spatial queries, or calculating distances in an environment of millions or billions of objects with minimal time expenditure. Indexing makes it possible to reproduce complex spatial scenarios in real time — for example, calculating traffic flows, modeling traffic jams, or predicting urban traffic behavior based on large archives of GPS tracks.

Methods for parallel processing of raster data, especially satellite images and surface models, which typically have tens of thousands of pixels per side, are of particular importance. Traditional operations—filtering, resampling, classification, segmentation, index calculation, or interpolation—are performed sequentially and are extremely resource-intensive. In the Big GeoData environment, distributed algorithms are used to split the raster into tiles, process them in parallel on cluster nodes, and combine the results into a single image. This approach is implemented in the RasterFrames, GeoTrellis, GDAL with multithreading, Earth Engine, and other cloud tools libraries. Parallel processing significantly reduces the time required to perform operations — from several hours to several minutes when working with satellite archives tens of terabytes in size.

In machine learning and deep analysis systems, geospatial data also requires high-performance computing. Preparing training sets for models of urban object segmentation, green area detection, vegetation classification, or LiDAR point cloud analysis requires the formation of large sample arrays When creating such models, batch generators are used, which combine data reading with high-speed decompression of raster tiles. Recent studies have shown that the use of GPUs and parallel data loading tools increases the speed of model training by 15–30 times compared to traditional CPU solutions. [88].

Another critically important area of high-performance processing is the analysis of LiDAR point clouds. In urban planning and spatial planning, such data is used to build detailed digital elevation models, reconstruct facades, determine building parameters, analyse green spaces, model shading, assess the impact of insolation, and create 3D models of the territory. LiDAR clouds can contain hundreds of millions or billions of points, requiring the use of accelerated algorithms, optimised data structures and parallelisation of processes. Common tools include PDAL, LAStools, Potree Converter, and CloudCompare with multi-threaded support. High-performance LiDAR platforms have been developed for use in cluster environments, including Entwine Point Tile (EPT), which allows point clouds to be stored and processed using a hierarchical pyramid with geospatial indexes. This allows for classification, filtering,

and normalisation of heights in streaming mode without loading the entire array into memory.

The application of Big GeoData in crisis monitoring and emergency management is of considerable interest. In such scenarios, it is particularly important to calculate areas of possible damage, analyse rapid changes in terrain and objects, detect damage using satellite images (e.g. change detection algorithms), and build predictive models of the spread of fires, floods or man-made disasters. High-performance processing enables such analyses to be performed in near real time, which is critical for decision-making. Studies show that the use of cloud services for emergency analysis allows operational maps to be generated 5-10 times faster than when using local systems [89].

The Cloud Optimised GeoTIFF (COG) format plays a special role in high-performance processing, allowing raster fragments to be read as needed without downloading the entire image. The format has become the de facto standard in the satellite industry and is widely used by NASA, ESA, USGS, Microsoft Planetary Computer, SentinelHub, and other data providers. In the vector environment, FlatGeobuf and Parquet-geometry formats play a similar role, focusing on streaming reading and distributed processing. These formats enable complex analytical tasks to be performed in Spark GIS, GeoMesa or BigQuery GIS environments with minimal overhead.

The synergy of these technologies — cloud platforms, GPU computing, distributed databases, optimised formats, and parallel processing algorithms — forms a new paradigm for working with geospatial data in municipal systems. It not only speeds up processing, but also allows you to integrate different types of data into complex models, maintain dynamic digital twins of territories, and perform long-term analysis and forecasting based on artificial intelligence. In this context, Big GeoData becomes not just a technological component of GIS, but a strategic tool for the development of territorial communities, digital transformation, infrastructure management, and ensuring the sustainability of the urban environment in conditions of rapid change.

3 ARTIFICIAL INTELLIGENCE METHODS IN GEODETIC DATA PROCESSING

3.1 Relevance of artificial intelligence technologies

The application of artificial intelligence (AI) technologies in geodesy is highly relevant and has great potential for improving the productivity, accuracy and efficiency of geodetic work. Machine learning can be used to solve the following problems:

1. Analysis and processing of geodetic data: AI can be used for automatic analysis of geodetic data, for example, processing measurement points, creating digital terrain models, etc. Artificial intelligence algorithms can help detect anomalies, recognise objects in images, perform calculations and automate data processing.

2. Automation of data processing. Surveying work requires a large amount of data processing, such as satellite images, laser scans, surveying measurements, etc. Artificial intelligence can automate this process by recognising and classifying objects in images, quickly calculating coordinates, and improving data processing accuracy.

3. Processing large amounts of data. Thanks to the speed and power of AI, large amounts of surveying data can be processed in a much shorter time. For example, analysing terabytes of surveying images to detect changes in the landscape can be done in minutes or hours, which previously took a lot of human resources and time.

4. Improved navigation and positioning (fig. 3.1). Machine learning can improve navigation and positioning accuracy by analysing data from satellites, sensors and other sources. Using machine learning algorithms, AI can correct measurements, compensate for noise, and correct errors, resulting in more accurate surveying results.
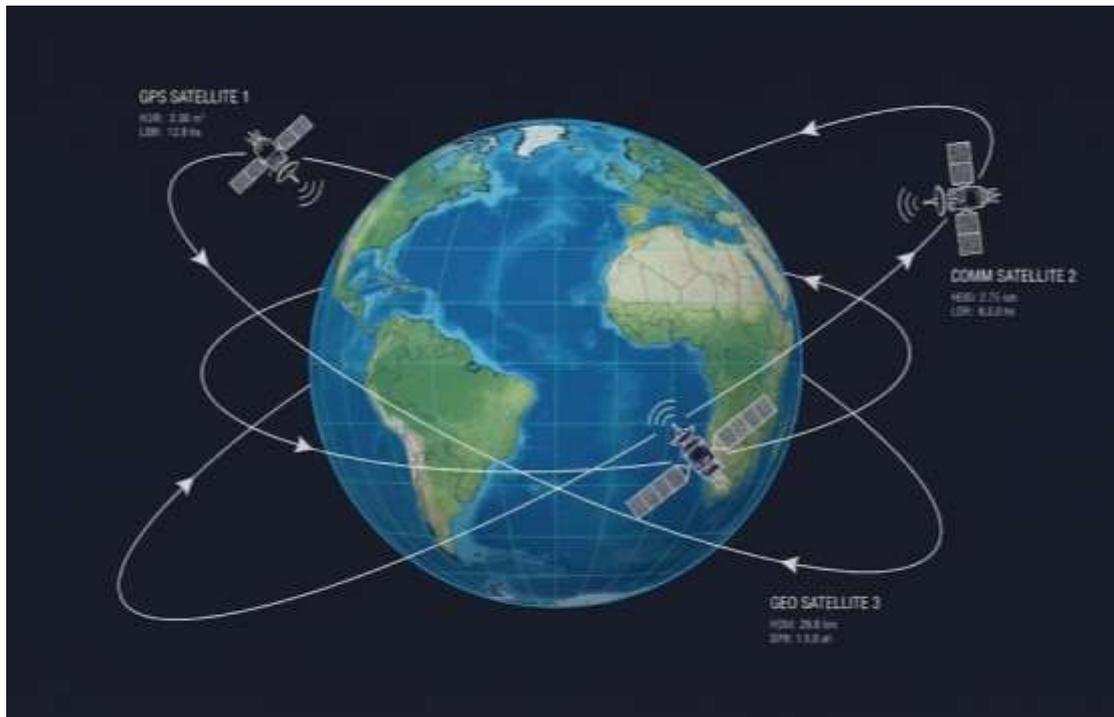
Fig 3.1 – Satellites around the Earth

5. Forecasting and modelling: AI can be used to forecast and model various processes related to geodesy and land management. For example, neural networks can be used to forecast changes in terrain or model hydrological processes. Predicting changes in the landscape. This technology can be used to predict changes in geodetic indicators such as ground surface movements, erosion, flooding, etc. AI can analyse large amounts of data from various sources to identify trends and develop models for predicting future changes.

6. Object recognition in images: AI can be used to automatically recognise and classify objects in images, such as buildings, forests, water bodies, etc. This can be useful when creating maps or assessing changes in the landscape.

7. Process optimisation: AI can be used to optimise various processes in surveying and land management, such as planning the optimal route for surveying or placing control points.

8. Expanding the capabilities of UAVs (fig. 3.2). The use of drones in geodesy is becoming increasingly widespread, and AI can improve their capabilities. For example, it can help drones automatically plan the optimal route for data collection, avoid obstacles, and automatically analyse the images obtained.
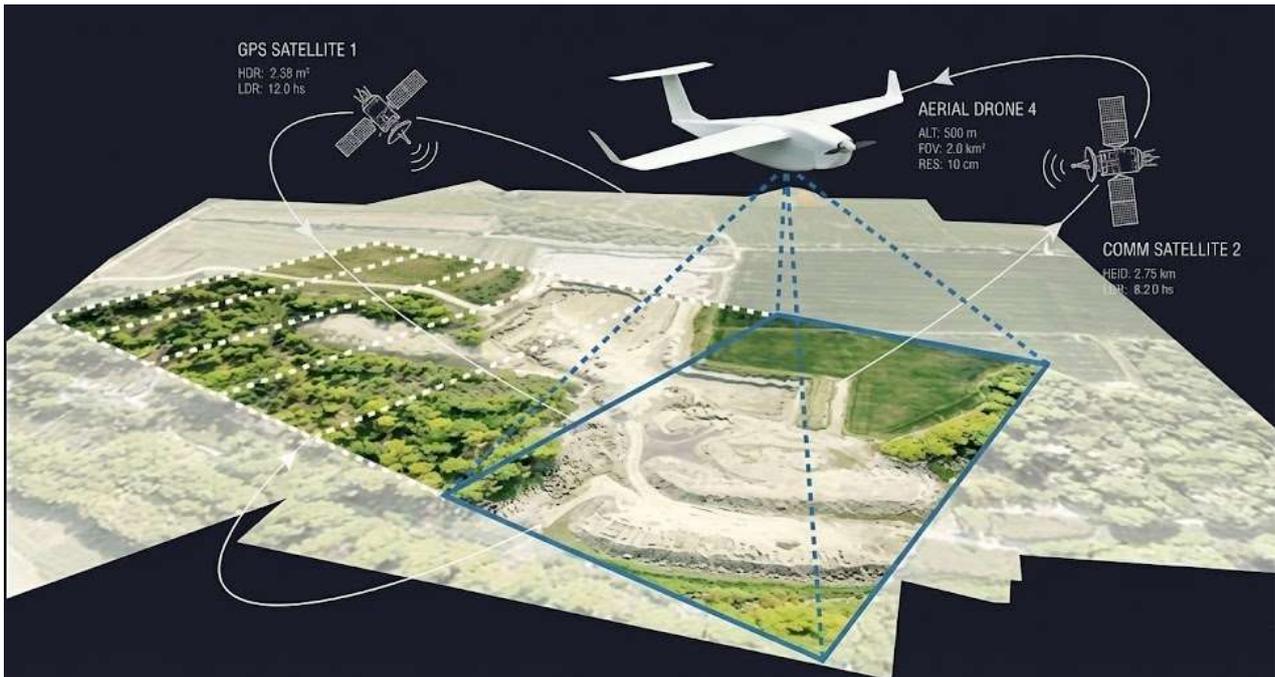
Fig. 3.2 – Example of UAV use

In general, the application of artificial intelligence technologies in geodesy opens up new opportunities for improving the quality and speed of geodetic work, contributes to more accurate results, and provides more convenient processing and analysis of geodetic data. The use of artificial intelligence in geodesy and land management can improve efficiency and provide new opportunities for automation and process improvement. [90].

3.2 Overview of existing methods for processing geodetic data

There are many methods of geodetic data processing that are used to analyse, interpret and obtain useful information from measurements. Traditional data processing methods include:

Triangulation – a method based on constructing triangular networks from measurement points to obtain the coordinates of objects (Fig. 3.3).
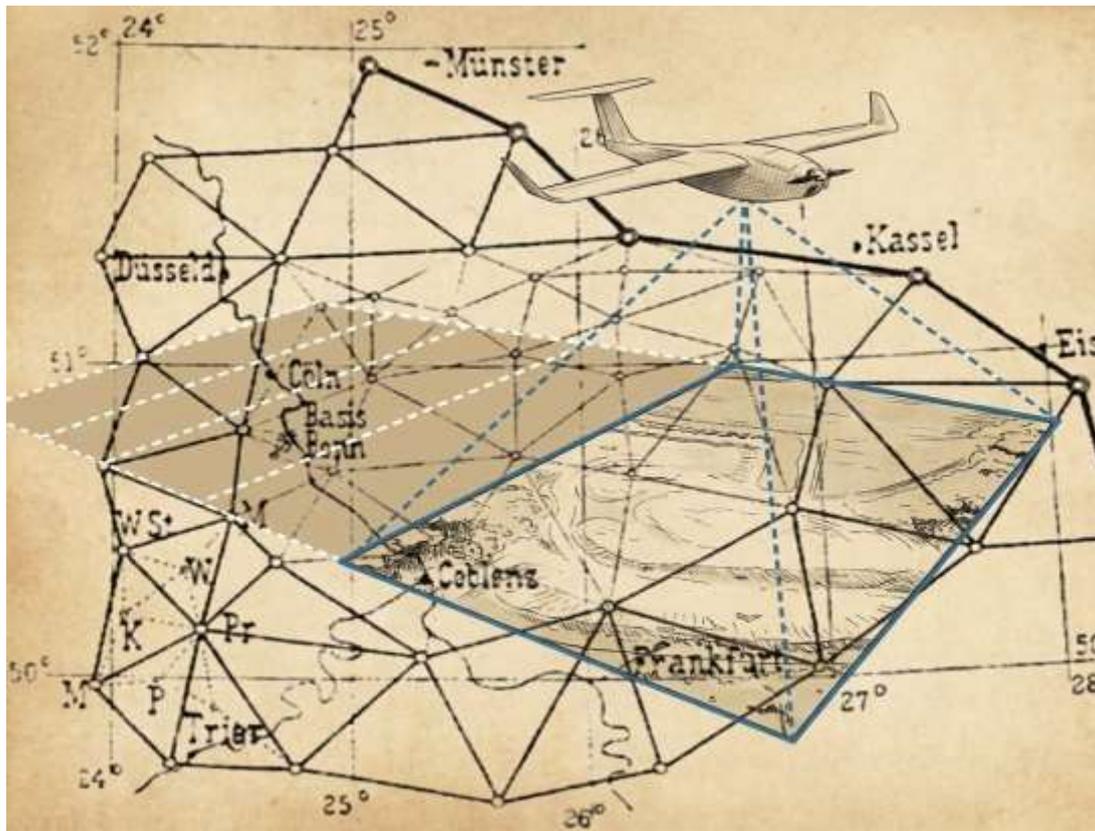
Fig. 3.3 – Illustration of the triangulation method

Trilateration – a method that uses distance and angle measurements to determine the position of objects.

Autocorrelation – a method used to analyse geodetic signals in order to identify patterns and regularities.

There are also less common methods of collecting and processing information, but they are no less important for the development of science.

Geodetic gravimetry is a method of measuring the Earth's gravitational field to obtain information about the geological structure and mass of the Earth. It is used to determine the heights and locations of geodetic points.

Laser scanning is the use of laser beams to measure distances and create an accurate three-dimensional image of the surface. It is used to create accurate terrain models, build 3D models of structures, and monitor changes in the landscape (fig. 3.4).
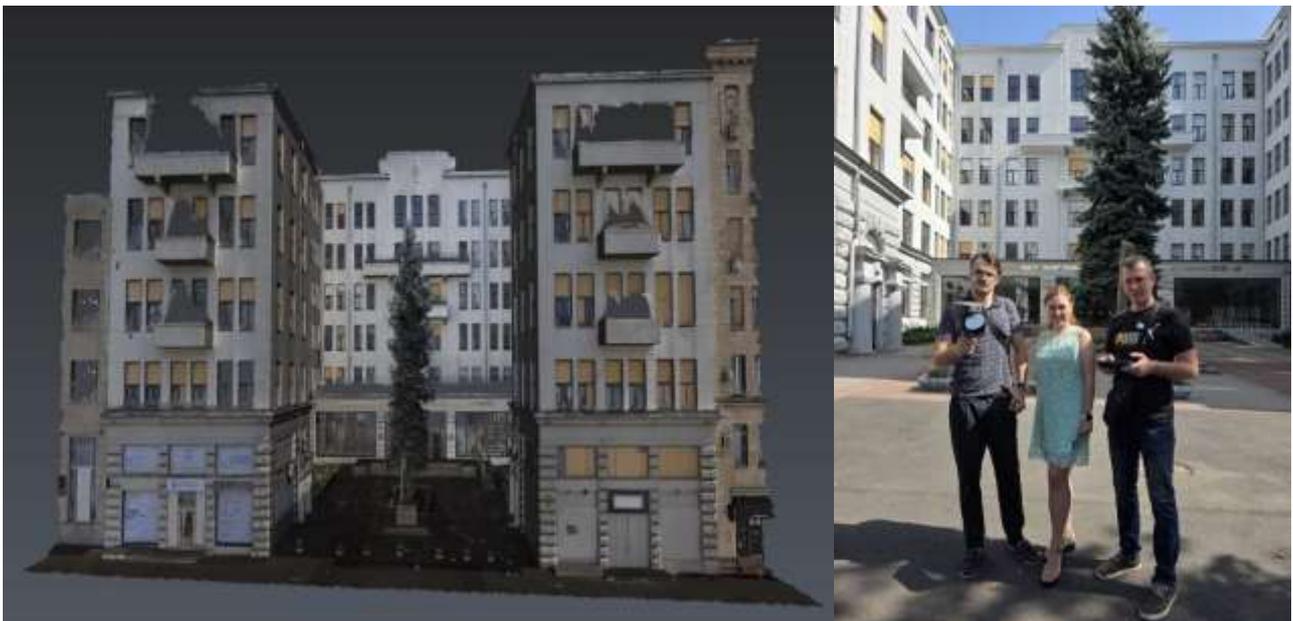
Fig. 3.4 – Application of laser scanning

Global Navigation Satellite System (GNSS): use of signals from satellites to determine the position of points on the Earth's surface. Methods such as the Global Positioning System (GPS) allow coordinates to be measured with high accuracy. [91].

Synthetic Aperture Interferometry (InSAR): using radio wave signals to measure distances between antennas on the Earth's surface. Used to monitor deformations of the Earth's surface, such as landslides, seismic activity and changes in elevation. (fig. 3.5).
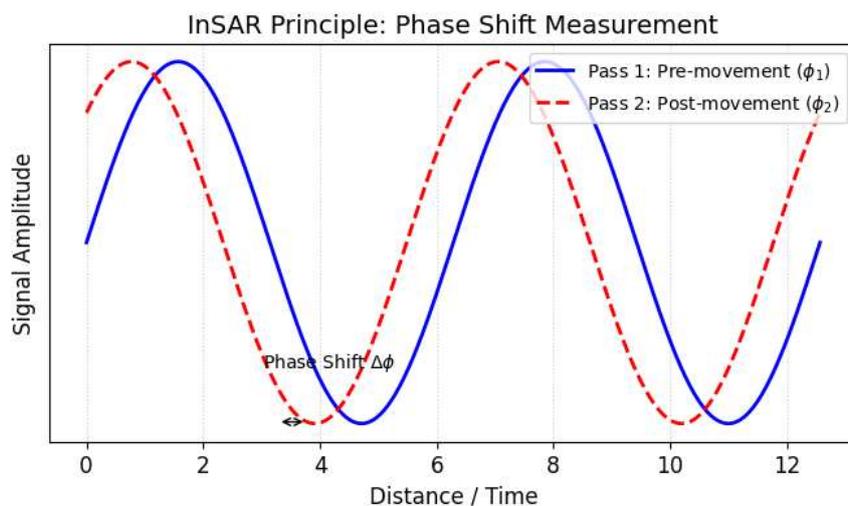
Fig. 3.5 – How InSAR works

Application of laser scanning

Global Navigation Satellite System (GNSS): use of signals from satellites to determine the position of points on the Earth's surface. Methods such as the Global Positioning System (GPS) allow coordinates to be measured with high accuracy.1 Synthetic Aperture Interferometry (InSAR): using radio wave signals to measure distances between antennas on the Earth's surface. Used to monitor deformations of the Earth's surface, such as landslides, seismic activity and changes in elevation. 1. How InSAR works. 1. These are just a few examples of geodetic data processing methods, as with the development of technology and the emergence of new tools such as artificial intelligence and deep learning, new methods are emerging that help improve the accuracy, speed and efficiency of geodetic data processing.

3.3   Analysis of approaches to developing methods for processing geodetic data using artificial intelligence

When developing methods for processing geodetic data using artificial intelligence, there are several approaches that can be applied. Here are a few of them:

Classification and recognition of objects. This approach involves training artificial intelligence models to recognise and classify different objects in geodetic images or vector data. For example, a model can be trained to recognise buildings, roads, water bodies, forests, etc. This can be useful when creating maps or assessing changes in the landscape. AI can be used to classify and recognise objects in geodetic images or LARS. Using computer vision and deep learning techniques, models can be developed that automatically identify types of objects such as buildings, roads, forests, etc.

Prediction and modelling. Artificial intelligence can be used to predict various parameters or model geodetic processes. For example, a model can be trained to predict changes in terrain, classify changes in work performed on a construction site, or model hydrological processes. AI can be used to predict changes in geodetic data, particularly in terrain. Using machine learning algorithms, it is possible to develop models that

predict erosion, landslides, changes in terrain, and other processes occurring on the Earth's surface.

Automatic data processing. Artificial intelligence can be used for automatic processing of geodetic data. For example, a model can automatically detect anomalies in data, correct errors, perform calculations, or determine measurement points. By applying data classification, segmentation, and filtering algorithms, geodetic data can be automatically processed and analysed.

Optimisation of geodetic processes. Artificial intelligence can be used to optimise various surveying processes, such as planning measurement routes, placing control points, optimising sensor locations, and so on. By applying optimisation algorithms and intelligent methods, it is possible to reduce the time and effort required to perform surveying tasks. For example, a model can help determine the optimal route for performing surveying work, optimise the placement of control points, or plan the location of survey areas.

These approaches can be applied separately or in combination with each other, depending on the specific requirements and tasks of the surveying project. An important step is to train artificial intelligence models on relevant data to achieve high accuracy and efficiency. The application of AI in this field can greatly facilitate and improve the processes of collecting, processing, and analysing surveying data.

When choosing approaches to developing methods for processing geodetic data using machine learning, the following factors should be considered:

- Determine the type of data. Consider the different types of geodetic data that can be worked with, such as satellite images, laser scans, measurements, etc. Determine what types of data will be used in the study and which machine learning methods are most suitable for processing this data.

- What specific tasks need to be solved using machine learning. For example, this could be the classification of objects in satellite images, determining the exact coordinates of objects, predicting changes in the landscape, etc. Each task may require the use of specific machine learning methods. [90].

- Assess the availability of data to achieve the research goal. Determine whether there is enough data to train machine learning models and conduct experiments. Determine whether preliminary data processing is necessary to prepare it for use in machine learning algorithms.

It is also necessary to select machine learning algorithms that correspond to the tasks and data types. We will consider algorithms such as neural networks, support vector machines, decision trees, clustering, etc. We will determine which algorithms are best suited for the task and data at hand.

Evaluate the effectiveness and limitations of using different machine learning approaches in the context of geodesy. Take into account processing time, computing power, the need for model training, and their real-time performance.

Pay attention to the practicality and feasibility of implementing the developed machine learning methods. Consider the availability of the necessary software tools, machine learning libraries, as well as your own skills and resources for implementing research.

Therefore, it is necessary to collect and analyse information about various machine learning approaches and methods, taking these factors into account. Focus your attention on those approaches that are best suited to achieving your goals.

3.4   Types of artificial intelligence algorithms

In artificial intelligence, there are several types of algorithms that are used to solve recognition, classification, prediction, and decision-making tasks. Several general types of artificial intelligence algorithms should be highlighted:

Logical algorithms. These algorithms are based on formal logic and rules. They are used to represent knowledge in the form of logical statements and rules and to make inferences based on these rules. Propositional logic systems and logical programming are examples of such algorithms.

Evolutionary algorithms. These algorithms mimic the processes of natural selection and evolution to solve problems. They use the concepts of genetic code,

populations, and selection to search for optimal solutions. Genetic algorithms and genetic programming are examples of evolutionary algorithms.

Supervised learning. Used to train models based on input data and corresponding labels or classifications. They are used for tasks such as classification, regression, and prediction. Examples of such algorithms are neural networks, support vector machines, and decision trees.

Unsupervised learning. Used to discover structures or patterns in input data without using labels or classifications.

Machine learning is used in many fields, from fashion to agriculture. Machine learning algorithms are capable of learning patterns and relationships between data, finding predictive information for complex problems, and extracting information that would otherwise be too difficult to find (fig. 3.6). Modern machine learning algorithms are capable of accurately processing large amounts of data in a relatively short period of time.
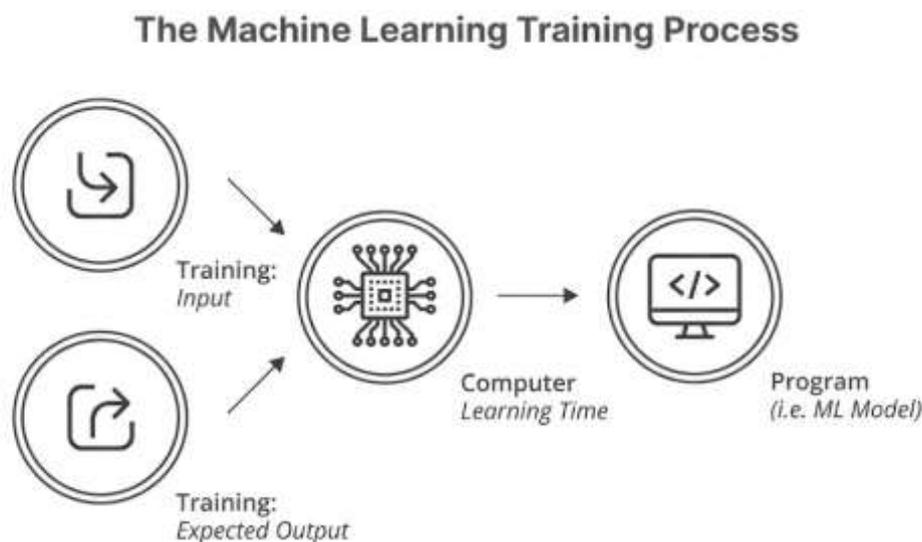
Fig. 3.6 – The machine learning process

There are several different types of machine learning algorithms, each with its own strengths and weaknesses. Some of the most popular include supervised learning (where the algorithm is provided with a set of training data), unsupervised learning (where the algorithm is provided with unlabelled data), reinforcement learning (where

the agent learns to associate positive and negative feedback with behaviour), deep neural networks, genetic algorithms, Bayesian networks, and so on. However, it is important to note that there is no single 'best' type of machine learning algorithm — each has its own advantages and disadvantages. Therefore, it is important to analyse all the different options available (fig. 3.7) before making a final decision.
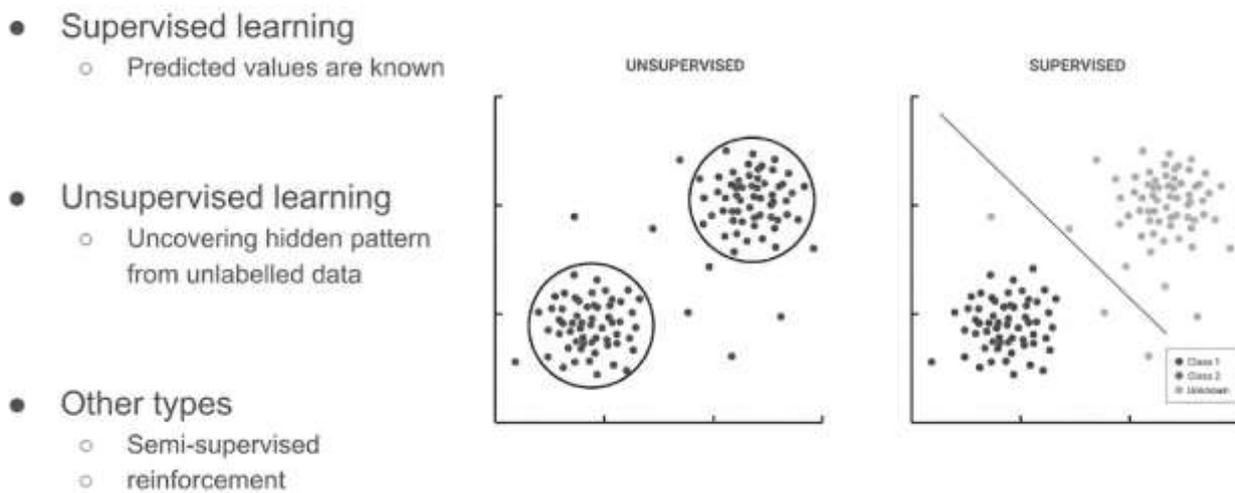
Fig. 3.7 – Types of machine learning

To train a machine learning algorithm, a large amount of labelled data is required — data that has been annotated with information about the different types of objects or events it contains. Unfortunately, this is often difficult to achieve. This is where datasets come in handy. Datasets are collections of carefully selected examples, specially prepared for use in machine learning research or applications [90].

3.5 The capabilities of artificial intelligence combined with AutoCAD software

Artificial intelligence and AutoCAD software can be combined to unlock advanced capabilities and deliver significant benefits in the field of design and project management (fig. 3.8).
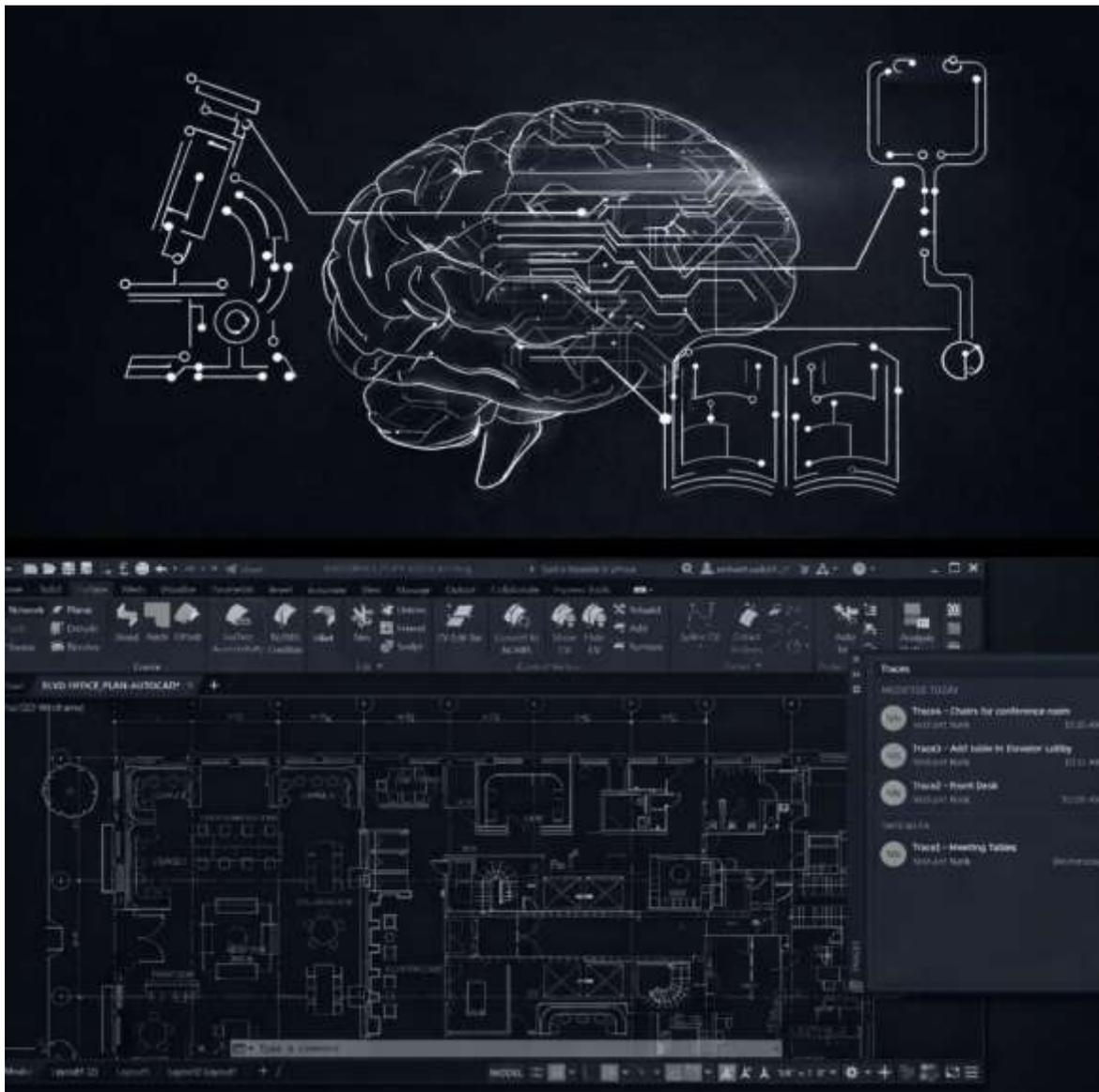
Fig. 3.8 – Combining machine learning with AutoCAD software

Automated recognition and processing of graphic elements. AI can be used to recognize and process geometric objects such as lines, curves, areas, etc. in AutoCAD software. This can simplify the processes of editing and modifying drawings, ensure accuracy, and reduce the risk of errors.

Automatic generation of drawings and documentation. The use of AI in conjunction with AutoCAD can help automate the process of generating drawings and creating documentation. For example, based on input data, AI can automatically create plans, dimensional drawings, specifications, etc., saving the designer time and effort.

Improved design accuracy and quality. AI can detect potential errors or inconsistencies in a design, helping to correct them before the final drawing is

produced. For example, an AI system can automatically check the correctness of connections, distances, scales, etc., ensuring high design quality.

Optimization of design solutions. AI can use machine learning algorithms to analyze large amounts of data and find optimal solutions. In AutoCAD software, this can mean automatically selecting the optimal location of objects, optimizing the project structure, etc.

Automated modeling and visualization. The use of AI in combination with AutoCAD can help automate the modeling and visualization processes of projects. AI can generate three-dimensional models based on two-dimensional drawings, create realistic visualizations, and virtual walks through the project.

It follows that the combination of artificial intelligence and AutoCAD software can improve design efficiency and accuracy, automate routine tasks, reduce the risk of errors, and improve the quality of projects in the field of surveying and project management. This opens up broad prospects for the further development and application of these technologies in this field.

3.6   Artificial intelligence in satellite image processing

Artificial intelligence is used to process satellite images in order to obtain valuable information about the Earth's surface. By combining machine learning algorithms, computer vision, and signal processing, AI can detect objects, classify them, perform image segmentation, identify changes in land cover, and perform many other tasks. Several specific applications of artificial intelligence in satellite image processing are worth noting:

Land cover classification. AI can be used to automatically classify different types of land cover based on satellite images. For example, a model can be trained to distinguish between forests, agricultural fields, water surfaces, urban development, etc. This allows for quick and objective information about the state of the land over a large area.

Change detection. AI can be used to automatically detect changes on the Earth's surface by comparing satellite images taken at different times. It can detect changes in the landscape, landslides, changes in the location of objects, etc. This is useful for monitoring environmental changes, developing local land use plans, and detecting natural disasters. Water resource analysis. AI can be used to analyse water resources, such as assessing water levels in rivers, lakes and ponds, detecting water pollution and evaluating the distribution of water resources in a given area. This helps to make decisions about the use and protection of water resources.

Crop forecasting. AI can be used to forecast crop yields based on analysis of satellite imagery and additional information about soil, climate, and vegetation. It can provide yield forecasts, providing farmers and agricultural businesses with valuable data for production planning and resource management.

Geodetic surveys. AI can be used to perform geodetic surveys by analysing satellite images and determining the exact location of objects on the ground. It can assist in calculating coordinates, measuring elevations, detecting changes in terrain, and modelling topographic features.

The examples presented demonstrate how artificial intelligence can be used to process satellite images to obtain valuable information about the Earth's surface. The use of AI in this field allows for the effective analysis of large amounts of data and provides fast and accurate information processing for decision-making in geodesy and land management.

Machine learning plays a significant role in the processing and analysis of satellite images. The following advantages can be cited in the application of machine learning in the processing of satellite images:

Image classification. Machine learning algorithms can be trained to classify satellite images into different categories, such as land cover types (e.g., forests, water bodies, urban areas) or to identify specific objects of interest (e.g., buildings, roads, agricultural fields). Such algorithms can be trained on labelled examples to automatically identify and classify features in images.

Object detection. Machine learning methods, particularly convolutional neural networks, can be used to detect and locate specific objects in satellite images. This is useful for applications such as identifying and tracking ships, vehicles, or infrastructure such as power lines and oil rigs.

Change detection. Machine learning models can be trained to detect changes between different satellite images taken at different times. By comparing pixel values or extracting relevant features, these models can identify areas where changes have occurred, such as deforestation, urban expansion, or natural disasters. This is important for monitoring and understanding land use dynamics and environmental changes.

Image segmentation. This method can be used to segment satellite images into separate areas based on the similarity of pixel values, texture, or other characteristics. This allows specific objects or areas of interest in the image to be identified. For example, segmentation can be used to delineate agricultural fields, water bodies, or forest boundaries.

Very high resolution. Satellite images obtained by lower-resolution sensors can be enhanced using machine learning methods. By training models on pairs of low- and high-resolution images, it is possible to generate satellite images with higher resolution, which helps to obtain finer details and more accurate analysis.

Atmospheric correction. Machine learning algorithms can be used to correct atmospheric effects on satellite images. These effects, such as light scattering and absorption by the atmosphere, can distort the spectral properties of the observed scene. By training models on atmospheric models and known ground truth data, machine learning can help eliminate these atmospheric artefacts and improve the accuracy of satellite image analysis.

Overall, machine learning methods play an important role in automating satellite image analysis, enabling faster and more accurate interpretation and supporting a wide range of applications in environmental monitoring, disaster response, urban planning, agriculture, and more.

An illustrated solution capable of automatically detecting and labelling crops can have a wide range of business applications. Calculating the number of land plots, their

average size, vegetation density, total area of individual crops, and many other indicators can serve various purposes. For example, government organisations can use these indicators for national statistics, while private farming companies can use them to assess their potential market in great detail.

The main task is to identify agricultural areas on satellite images. For this purpose, an unprocessed Sentinel-2 image is used: 10,000 x 10,000 pixels, each pixel representing 10 x 10 metres on the ground, Copernicus Sentinel data for 2019 (fig. 3.9).
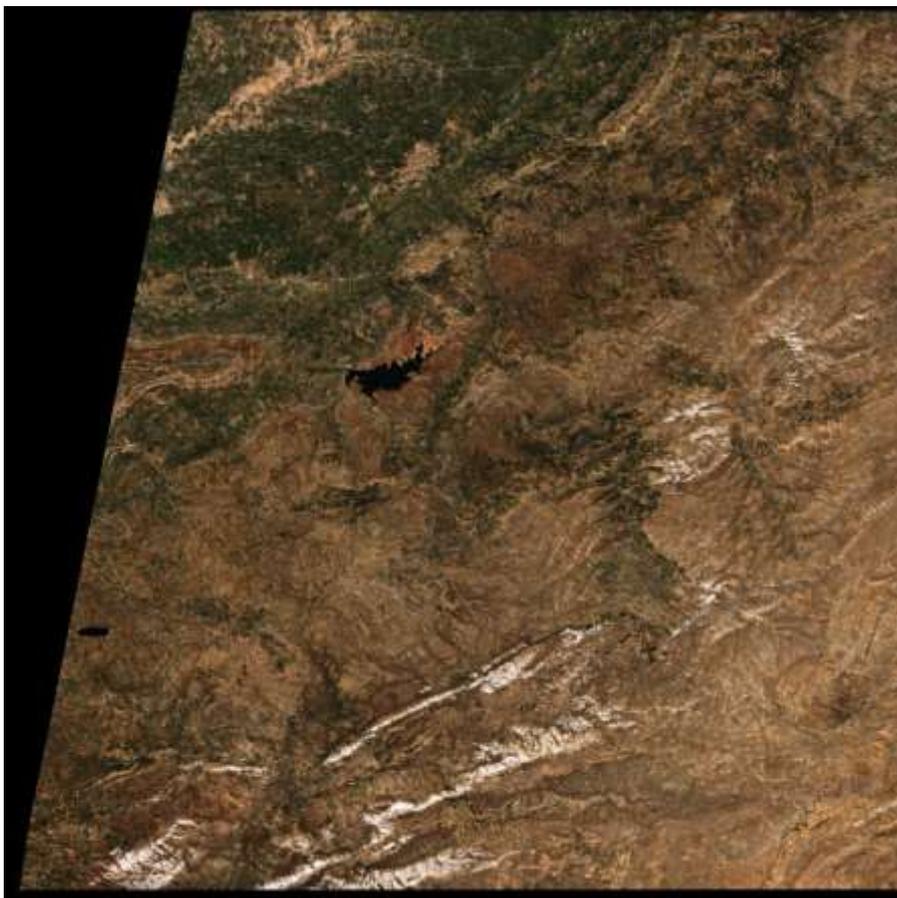
Fig. 3.9 – Unprocessed image

As a result of the preliminary processing of Sentinel 2 images, the first task is to find areas and limit them to specific areas of interest. Each image has a very high resolution, so it would be unrealistic to apply full processing to full-size images. Instead, the first step towards a solution is to crop large images into smaller fragments

and identify the areas where the sites were located on these smaller images. As a result, fragments containing only agricultural areas are identified (fig. 3.10).

Fig 3.10 – A separate fragment of a satellite image

The solution for identifying agricultural areas in large images is to create a pixel classifier. For each pixel, this machine learning model will predict whether the pixel belongs to a forest, city, water, farm, and therefore to an agricultural area or not (fig. 3.11).

Fig. 3.11 – Illustration of pixel classification

We obtain an image with pixel classification into three visible pixel classes (sand, vegetation, buildings). Since many objects can be found on a satellite image, the image can identify labels with more than 10 different classes of ground truth (forest, water, pine needles, etc.). However, if the climate of your study area differs from the area where you trained your model, you may need to re-evaluate the classes assigned to each pixel.

For example, after training the model in countries with a temperate climate and applying it to more arid regions of the world, it becomes apparent that what the model saw as forests and tundra were actually agricultural crops.

After classifying the pixels, it is possible to remove all images that do not contain any agricultural land.

The next step is to identify and delineate agricultural areas, i.e., to create an uncontrolled edge detector. Once the location of agricultural areas has been determined, we began to focus on delineating individual plots within these specific areas.

Due to the lack of labelled data, an unsupervised approach based on Canny Edge detection in Open CV is used. Edge detection involves looking at a specific pixel and comparing it to the pixels around it. If the contrast with neighbouring pixels is high, the pixel can be considered an edge (fig. 3.12).

Fig. 3.12 – Example of edge detection in agricultural areas using

Open CV

Once all pixels that could potentially be real edges have been identified, the next step is to smooth the edges and form polygons. It is expected that the edge detection algorithm will be much more effective when applied to large areas (fig. 3.13).
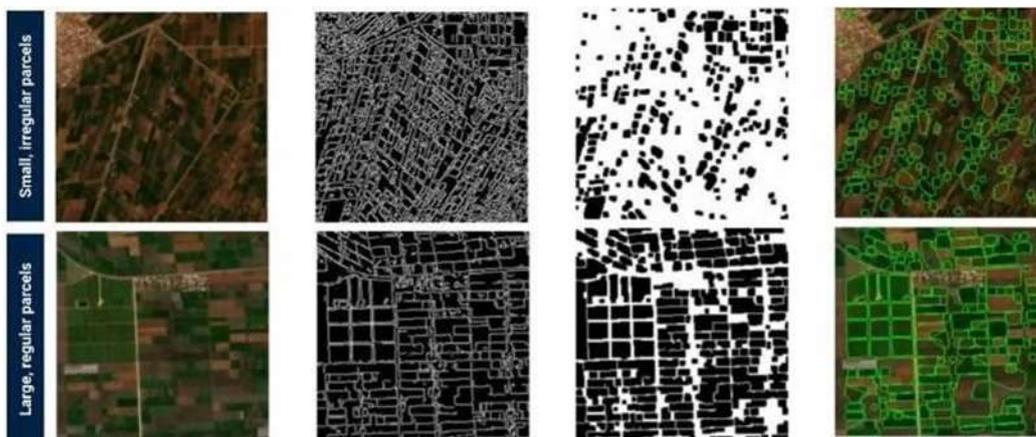
Fig 3.13 – Illustration of the complete process of delineating areas

This method allows for the automatic identification of approximately 7,000 areas in the study zone. Since the pixel classification method is used, it is possible to separate the actual farm areas from other polygons, thus retaining only the relevant data.

To obtain the best possible results, it may be useful to apply changes to a single image, in particular by playing with contrast, saturation or sharpness (fig. 3.14).
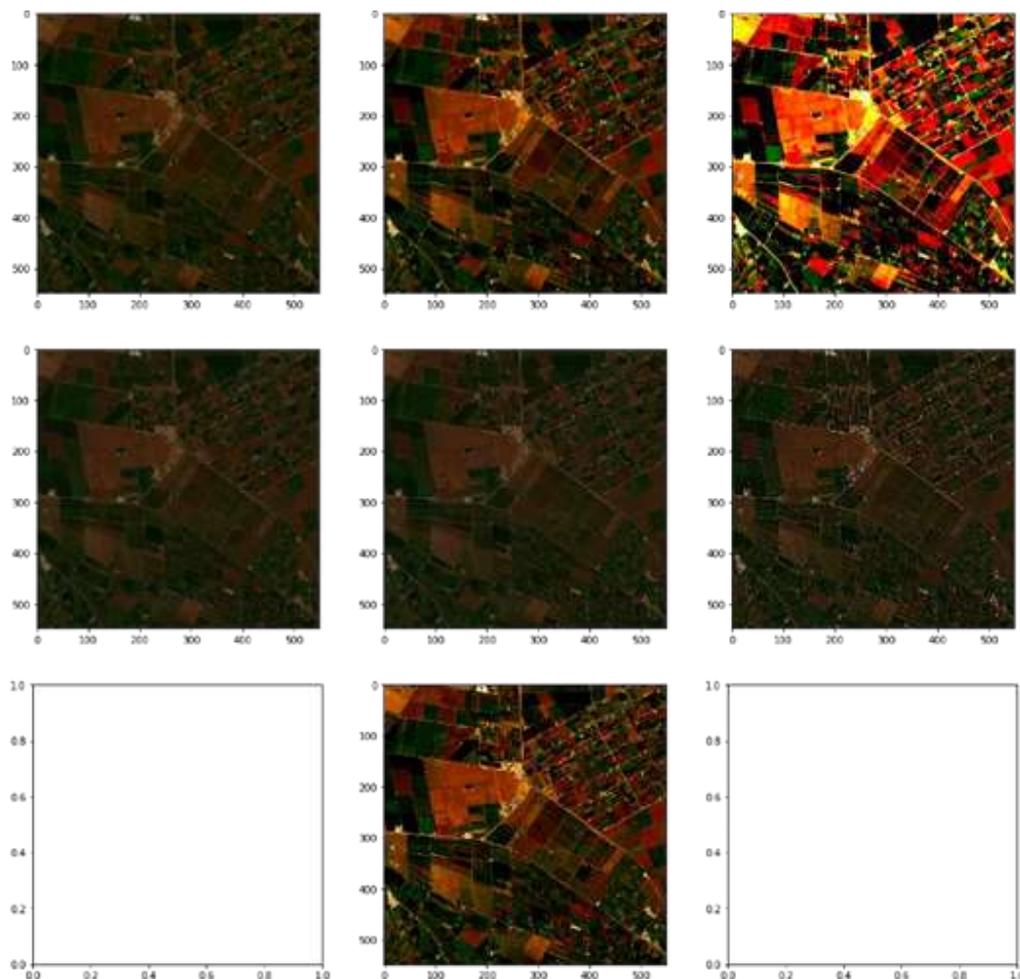
Fig 3.14 – Optimising the boundary detection algorithm

Experimenting with contrast, saturation or sharpness can help improve edge detection.

Another important optimisation factor is the convexity of polygons. Most regular-shaped graphs using convex polygons usually give much better results. To achieve this, the forced formation of convex land parcels is used (fig. 3.15).
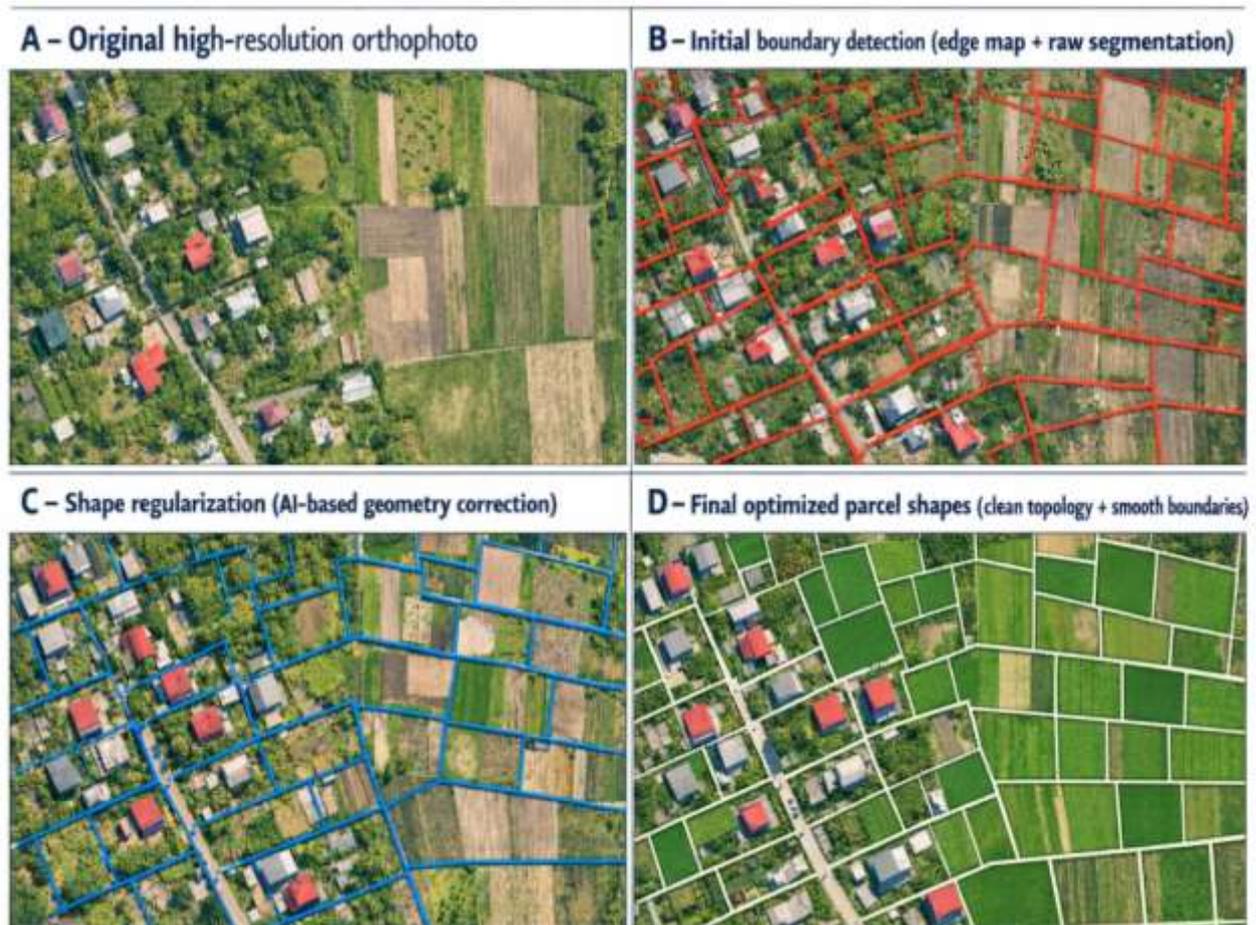
Fig. 3.15 – Optimisation of land parcel shapes

Thus, working with satellite imagery opens up endless possibilities. Considering how each satellite image provides different functions, as well as how the availability and format of additional data may vary around the world depending on the area of study, each individual project will be a unique use case.

3.7 Integration of artificial intelligence methods into surveying production processes and municipal GIS

The practical significance of artificial intelligence methods in surveying and geospatial data processing is only fully realised when these methods are integrated not in a fragmented way, in the form of separate experimental modules, but as integral production processes embedded in the functioning of geodetic services, cartographic departments and municipal GIS. In other words, the key task is not only to develop

separate models for classification, segmentation or deformation prediction, but also to construct stable workflows where data, algorithms and management decisions are linked into a single intelligent ecosystem. In this section, integration will be understood as the systematic implementation of AI at all stages of the surveying cycle — from planning measurements and field data collection to their office processing, uploading to municipal GIS and using the results in urban planning, land management and engineering infrastructure management processes.

A generalised diagram of such integration can be presented as a sequence of interconnected blocks:

1) data sources (GNSS, UAVs, ground-based and mobile laser scanners, satellite platforms, InSAR, engineering network sensors);

2) pre-processing and quality assurance module (calibration, filtering, topological and semantic validation);

3) intelligent processing module (machine and deep learning models for classification, segmentation, change detection, forecasting);

4) geoinformation integration module (recording in geodatabases, layer updates, visualisation and spatial analysis);

5) decision support module, where analytics results are transformed into urban planning regulations, cadastral actions, engineering solutions or risk management scenarios. This structure is consistent with modern GeoAI approaches, which emphasise the need for a close combination of spatial data models, AI algorithms and service-oriented GIS architectures [92].

In surveying practice, AI integration begins at the stage of planning and organising field work. Intelligent models can be used to optimise the location of reference points, select the configuration of GNSS measurement routes, and determine the optimal trajectories of UAVs, taking into account terrain, buildings, restricted areas, as well as predicted lighting conditions and meteorological factors. Optimisation and reinforcement learning algorithms allow the creation of survey plans that minimise the total length of routes, fieldwork time and resource consumption, while ensuring the

required level of accuracy and measurement redundancy. In fact, at this stage, AI is already becoming a tool for 'smart planning' of geodetic projects.

At the data collection stage, particularly when using UAVs and mobile mapping platforms, AI integration is implemented through computer vision systems that analyse video streams and operational orthophotos in real time, identifying gaps in coverage, areas with insufficient image overlap, and areas with a high risk of artefacts (reflections, shadows, glare). In the case of laser scanning, machine learning models can immediately perform preliminary classification of point clouds (separating soil, vegetation, buildings, and engineering structures), which significantly reduces the amount of subsequent office processing. For GNSS receivers, promising approaches involve deep learning models that correct positioning results based on local signal reception conditions, satellite constellation geometry, and environmental characteristics, forming so-called 'intelligent corrections' to coordinates.

The potential of AI is most fully realised at the office stage, where geodetic measurements are integrated with remote sensing data, urban planning documentation, cadastral information and other sources. For LiDAR point clouds, deep learning models are used to perform multi-class classification of each point according to its belonging to the ground surface, buildings, engineering infrastructure, vegetation of various types and height categories [93]. For orthophotomaps and satellite images, convolutional neural networks are used for semantic segmentation, which automatically form vector layers of buildings, roads, green spaces, water bodies, and auxiliary infrastructure. This results in semi-automated workflows in which the engineer's role is not so much to manually digitise the geometry as to validate the results, correct errors, and adjust the hyperparameters of the models.

The issue of quality and reproducibility of results is particularly important, since the integration of AI into production processes requires not only high accuracy, but also transparency of methods, the ability to audit and repeat calculations. In this context, it is advisable to implement the MLOps (Machine Learning Operations) approach, which involves managing the entire life cycle of models — from collecting and annotating training data to deployment, versioning, quality monitoring, and regular retraining. For

surveying and municipal practice, this means that each intelligent model (orthophoto classifier, point cloud segmenter, deformation prediction model, etc.) must be accompanied by a description of the version, parameters, training samples used, data time intervals, and quality indicators (accuracy, completeness, F1-measure). This ensures the comparability of models, reproducibility of results, and compliance with the principles of academic integrity and regulatory requirements.

The integration of AI into municipal GIS also requires a well-thought-out architecture at the software and hardware infrastructure level. As a rule, several levels are formed:

1) data storage level (spatial DBMS such as PostGIS, raster data repositories, cloud archives of satellite images);

2) processing and analytics level (GIS servers, computing nodes for running AI models, cloud services such as Google Earth Engine or proprietary cluster solutions);

3) services level (REST-API, WMS/WFS/WCS, analytics and forecasting services);

4) user interface level (web maps, control panels, mobile applications, analytical dashboards). In this case, artificial intelligence models are deployed as microservices that GIS applications access as needed — for example, to automatically classify new orthophotos, forecast deformations for the coming months, or assess the risk of flooding based on updated precipitation and water level data [94].

The role of humans in integrated geodetic processes using AI is no less important. Despite the high level of automation, the success of such systems depends on the competence of the engineer who defines the task, quality criteria, validation rules, and interpretation of results. The human-in-the-loop concept assumes that engineers not only control the operation of models, but also actively influence their training: they correct classification errors, supplement training samples, formulate new features, and adapt models to the local specifics of the territorial community. This is especially important in situations where surveying and urban planning decisions have legal implications, and the results of geodata processing can affect property rights, planning regimes, land use restrictions, and engineering regulations.

Thus, the integration of artificial intelligence methods into geodetic production processes and municipal GIS should be viewed not as a one-time 'algorithm implementation,' but as a long-term process of building an intelligent spatial infrastructure in which data, models, services, and management decisions are interconnected in a single cycle. This approach provides the opportunity to systematically improve the efficiency of geodetic work, reduce the time required to update spatial information, increase the accuracy of urban planning and cadastral decisions, and creates a reliable basis for the formation of digital twins of territorial communities and intelligent urban space management systems.

The integration of artificial intelligence technologies into production surveying processes is particularly effective in monitoring the technical condition of engineering structures and critical infrastructure. Traditional methods of determining deformations were based mainly on periodic geodetic observations, between which there were significant time intervals. This approach provided only a discrete picture of the development of displacement or subsidence processes in buildings and structures. In contrast, the use of satellite interferometry (InSAR), continuous time series from GNSS stations, and local sensor networks opens up the possibility of almost continuous monitoring, in which artificial intelligence models allow complex, often uneven processes to be analysed. Deep recurrent networks, capable of detecting hidden dynamic patterns in changes in the position of objects, as well as transformer-based models, which provide increased accuracy in predicting nonlinear and sudden changes in geodynamic parameters, are particularly effective [95.].

In urban environments, integrating AI methods into geodetic monitoring systems allows for the creation of highly accurate risk zone maps that are automatically updated as new data becomes available. For example, combining InSAR data with LSTM-based predictive models makes it possible to identify dangerous soil movement trends long before they can be detected by visual inspection or traditional geodetic surveying methods. For engineering communications (water supply, sewerage, heating networks), artificial intelligence systems are capable of integrating information from observations of soil subsidence, temperature changes, and vibration characteristics,

creating comprehensive models of the network's condition that automatically signal the risk of pipe breaks or critical deformations. Such approaches have already been tested in a number of European cities, where GeoAI systems are included in the structure of digital twins of urban infrastructure [68].

An important component of AI integration is ensuring compatibility and interoperability between different software platforms used in surveying and mapping activities. Modern GIS — ArcGIS Pro, QGIS, PostGIS, Bentley OpenCities, Autodesk Civil 3D — support the ability to connect external machine learning models via REST interfaces, Python API, cloud services, or Docker containers. This allows you to create scenarios in which certain actions are performed automatically after new data is received: for example, downloading a new orthophoto from a UAV can automatically launch an intelligent module for building segmentation, and updating GNSS data can launch a predictive model to estimate changes in elevation marks. Thus, GIS becomes not only a platform for visualising and storing data, but also the core of an intelligent production infrastructure.

In the practice of local communities, the integration of AI into geodetic processes is of particular importance due to the need for prompt updating of cadastral data, monitoring of buildings, analysis of land use and detection of violations. Automatic object detection systems on satellite and aerial photographs allow the detection of new buildings, illegal extensions, unauthorised landfills, changes in vegetation and the condition of road infrastructure. Combining these algorithms with data on urban planning conditions and restrictions, in particular zoning rules and building codes, allows for the generation of automatic alerts about potential violations of building regulations. For rural communities, machine learning algorithms can analyse the structure of agricultural land use, identifying undeclared cultivated areas and changes in crop types, which significantly expands the capabilities of communities in the field of land use control [97].

The combination of artificial intelligence technologies with the concept of a digital twin of the territory is of particular importance. In this case, geodetic data serves as the basis for creating a multidimensional model that integrates indicators of relief,

buildings, engineering infrastructure, transport flows, environmental characteristics, and socio-economic data. Artificial intelligence ensures dynamic updating of the digital twin, automatic inclusion of new observations, and forecasting of development scenarios, which is key to managing territories that are rapidly changing or are under the influence of external factors such as military actions, man-made accidents, and climate change. The introduction of such systems into the activities of Ukrainian territorial communities creates a fundamentally new quality of spatial development management.

The issue of standardising the processes of integrating AI into geodetic and municipal systems is particularly important. Given the critical nature of geospatial data and its impact on property rights, land use regulation, and engineering decisions, it is necessary to implement the principles of transparency, reproducibility, and accountability when using intelligent models. The international standards ISO 19100, INSPIRE and OGC recommend clear approaches to semantic consistency, topological correctness, attribute quality and geodata change history management — and AI must operate within this regulatory framework. In the long term, it is important to envisage the creation of local standards for the use of AI in cadastral and geodetic activities, in particular regarding acceptable model errors, training sample requirements, audit protocols and responsibility for automated decisions.

The deepening integration of artificial intelligence into geodetic production processes also creates new requirements for the competencies of specialists. Modern surveyors must possess not only classic skills in field measurements, office processing and regulatory and legal support, but also basic machine learning methods, principles of neural network models, big data processing methods, Python programming basics and MLOps practices. University programmes must adapt to this challenge by integrating disciplines such as GeoAI, Spatial Data Science, Deep Learning for Geospatial, AI-based LiDAR point cloud processing, automation of geodetic processes, and the creation of digital twins.

In summary, the application of artificial intelligence in production surveying processes and municipal GIS should be seen as a transition to a new paradigm of spatial

management, where geodata, analytics, and management decisions form a single intelligent system. It is based on the principles of automation, high accuracy, adaptability, and self-learning, which significantly improves the efficiency of geodetic work, optimises land planning, increases the safety of engineering structures, and ensures transparency in land management and urban planning decisions.

3.8   Automation of production processes based on artificial intelligence

The digitisation of surveying and mapping processes has led to the emergence of a new professional category — the 'digital surveyor,' who combines the traditional competencies of a surveying engineer with skills in working with artificial intelligence systems, automated analytical platforms, cloud computing, and high-performance geospatial data processing tools. The evolution of the role of a surveyor from a measurement operator to an intelligent data analyst is explained by the transformation of the entire industry, where modern methods of collecting, modelling, and interpreting geospatial information cannot be effectively implemented without the use of machine learning and deep learning algorithms. The emergence of the 'digital surveyor' is not only a matter of technical modernisation, but also a key condition for the adaptation of the surveying industry to the requirements of Smart City concepts, digital twins, geoanalytics and intelligent territory management systems [98].

The basis of a digital surveyor's professional activity is the construction of integrated intelligent production flows (AI-driven workflows), in which data is collected, processed and analysed with minimal manual involvement. In the classic approach, field surveying, office processing, topographic material formation, GIS layer preparation, and result validation were carried out sequentially and often separately. The modern concept of a digital surveyor involves a single integrated data processing line, where all stages are linked by intelligent modules based on machine learning, automated quality control systems, and cloud computing platforms. This approach ensures the continuity of the production process, shortens the cycle of spatial product creation, and increases the accuracy of the final results.

An important element of a digital surveyor's work is the automation of data collection using intelligent UAV platforms, mobile mapping systems, multi-frequency GNSS receivers, and new-generation laser scanners. In modern multimodal systems, flight tasks for UAVs are generated using optimisation and reinforcement learning algorithms that take into account the terrain, orientation of the territory, building density, probability of shadow zones, presence of flight restriction zones, and predicted changes in weather conditions. During flight, the computer vision model can automatically adjust the route to eliminate gaps in coverage, and the real-time orthophoto pre-classification system determines the optimal exposure and camera orientation parameters. During ground-based laser scanning, deep neural networks are capable of classifying surfaces at the point collection stage, separating ground models, infrastructure objects, green spaces, and other elements, which significantly reduces the time spent on subsequent camera processing [99].

During the indoor stage, the digital surveyor uses GeoAI tools for automated filtering, normalisation, classification, and segmentation of data. Neural network architectures U-Net, DeepLabV3+, FCN, and Mask R-CNN provide automatic recognition of buildings, road objects, terrain features, and green belts on orthophoto maps, which significantly speeds up the process of creating vector layers for municipal GIS [100]. LiDAR point clouds are processed using PointNet++, RandLA-Net, and KPConv models, which allow for the automatic classification of objects even in high-noise or complex urban structures.

Importantly, digital surveyors work not only with geometry but also with extended semantic structures that provide comprehensive analysis of territories. Modern methods include multi-level interpretation of geodata: recognition of cover types, analysis of structural characteristics of urban morphology, detection of anomalies in relief or building characteristics, and identification of areas of potential risk. All these processes take place in automated modules, where the surveyor acts as an analyst and auditor of results, rather than a performer of routine operations. This approach significantly increases productivity and minimises the influence of subjective factors, which is especially important when creating cadastral maps, updating urban

planning documentation, controlling development, and managing the land resources of local communities.

A separate area of activity for digital surveyors is participation in the creation and operation of digital twins of territories. In such systems, GNSS, InSAR, LiDAR and Earth remote sensing data are fed into a single model, where they are processed using forecasting models (LSTM, GRU, Temporal CNN, Transformer-based forecasting architectures). The result is a multidimensional model of the territory that is automatically updated and reflects the state of the relief, buildings, transport flows, engineering infrastructure and environmental characteristics. The role of the surveyor is to ensure the spatial accuracy and validation of all components of the digital twin, making the specialist a key figure in strategic spatial planning working groups [101].

An equally important component of the new profession is mastering data processing automation tools — Python, R, QGIS Processing, ArcGIS ModelBuilder, FME, cloud GPU clusters, Google Earth Engine. A digital surveyor must be able to build their own pre-processing algorithms, create pipelines, optimise calculations, and manage the full life cycle of artificial intelligence models. This requires knowledge of MLOps approaches: model versioning, dependency control, quality monitoring, regular retraining, and execution infrastructure management. These requirements are fundamentally new to the industry and determine the strategic direction of modernisation in education and training.

In fact, a digital surveyor is a key figure in the ecosystem of intelligent geodata processing, combining technical precision, spatial thinking, big data analytics, algorithmic design, and engineering responsibility. This role goes beyond traditional surveying and covers the fields of urban planning, cadastre, environmental monitoring, risk management, engineering, and digital modelling of territories. Therefore, the formation of a digital surveyor is not just a technological trend, but a fundamental condition for the transition to a new paradigm of spatial management, where artificial intelligence is an integral part of surveying science and practice.

The key principles of the digital surveyor concept also include the ability to work with complex flows of heterogeneous data that combine traditional surveying

measurements with alternative sources of information — crowdsourced data, mobile sensors, mobile operators' geolocation services, data from satellite IoT platforms, and open public registries. The use of such data significantly expands the range of possibilities for spatial analysis, but at the same time requires intelligent means of coordination, normalisation, and quality control. In this context, artificial intelligence models that can automatically detect mutual inconsistencies between individual sources, assess the degree of confidence in information, substitute for gaps, and determine probable limits of uncertainty are particularly important. Deep ensemble learning and Bayesian neural network methods enable the formation of forecasts with an indication of their probability level, which is critically important for cadastral, urban planning and engineering decisions, where errors can have significant legal consequences [102].

The integration of artificial intelligence technologies into the production activities of the geodetic departments of local communities creates the conditions for building fully automated systems for monitoring the state of territories. Such a system may include automatic updating of terrain information based on UAV and LiDAR data, regular analysis of Sentinel-1/2 satellite images for changes in land use, automatic detection of illegal construction, tracking of urbanisation and degradation of green areas, flood monitoring based on radar interferograms, and emergency risk forecasting. All these components merge into a single intelligent platform that provides local communities with access to up-to-date cartographic materials, analytical models, and recommendations for decision-making in a mode that is as close to real time as possible [103].

Digital surveyors play a particularly important role in engineering monitoring projects involving bridges, overpasses, tunnels, high-rise buildings, and hydraulic structures. In the context of climate change, increasing loads on engineering infrastructure, and more frequent extreme events (flooding, landslides, seismic activity), automated monitoring systems are becoming critically important. Based on integrated data from GNSS observations, InSAR signals, strain gauges, laser scanners, and hydrological sensors, digital surveyors build predictive models that allow them to

assess the risks of structural deformation and make decisions aimed at improving safety and extending the service life of structures. Such predictive models demonstrate significantly higher accuracy compared to classical approaches, as they are capable of taking into account nonlinear dependencies and complex interactions between environmental factors [104].

At the same time, the profession of digital surveyor also presents new ethical and regulatory challenges. Since the results of artificial intelligence modeling can influence legally significant decisions in the fields of urban planning, land management, environmental protection, and critical infrastructure management, there is a need to ensure model auditing, decision traceability, and algorithm verification. The principles of "transparent AI" are particularly relevant because they allow engineers and municipal officials to understand why a model has made a particular decision, assess the risks of errors, and gain the trust of users and regulators. This is crucial in geodetic and cadastral procedures, as decisions must be legally verified and based on a comprehensible algorithmic process rather than a "black box." [105].

An important element of a digital surveyor's work is also data quality management in accordance with international standards ISO 19157, ISO 19115, INSPIRE Data Quality Guidelines, and OGC standards. The Data Quality by Design approach assumes that artificial intelligence systems should not "patch" problems with poor input data, but should work with data that is already high-quality, correctly structured, and semantically consistent. The digital surveyor acts as a guarantor that all data entering GeoAI processes undergoes proper filtering, topological control, semantic verification, and spatial consistency, which is the basis for building accurate models and avoiding the accumulation of systemic errors in GIS [106].

An equally important task for digital surveyors is to participate in the development of policies for managing geospatial data and the spatial infrastructure of local communities. In today's environment, communities are increasingly moving towards a model of 'geospatial management,' where decision-making is based on an integrated picture of the state of the territory, created on the basis of intelligent analysis. This applies to urban planning, land resource management, environmental risk

forecasting, transport planning, public administration, and monitoring of strategic development programmes. Digital surveyors provide the level of accuracy, validation and analytical quality that enables communities to become full participants in digital transformation, capable of data-driven governance.

Ultimately, the emergence of the digital surveyor is a fundamentally important element in the restructuring of the surveying industry towards automation, intellectualisation and increased accuracy of spatial analysis. This is not only a new professional role, but also a new paradigm — multi-level, integrated, automated and supported by artificial intelligence analytics. It allows us to move from fragmented processes to a holistic intellectual geospatial infrastructure in which the geodesist acts as the central agent of digital transformation.

The intellectual ecosystem of the digital surveyor involves not only changes in the methods of collecting and processing geospatial data, but also a fundamental rethinking of approaches to storing, using and managing data throughout its life cycle. In traditional systems, geospatial information was stored in the form of separate layers, models and office reports, which were periodically updated during new survey cycles. Modern digital geodesy is moving towards the concept of 'live' data, which is constantly fed into the system from sensors, satellites, UAVs, crowdsourcing platforms and field mobile applications. Under these conditions, the role of the surveyor is to ensure the spatial and temporal integrity of these flows, to build data synchronisation mechanisms and to control their relevance, since relevance is a critical parameter in operational monitoring systems and digital twins.

Within the new paradigm, digital surveyors actively use the concepts of geospatial cloud data centres and distributed computing. New-generation geospatial databases — such as PostGIS, SpatiaLite, GeoMesa, TileDB, and cloud-native formats (COG, Zarr) — allow data processing to be scaled up to the level of national infrastructures or large territorial communities. Integration with intelligent services enables automatic updating of relief models, recalculation of earthwork volumes, analysis of cultivated areas, monitoring of water resources, or assessment of the condition of the street and road network. In such systems, a digital surveyor is not just

a user of a geodatabase, but an architect of complex structures for storing and accessing geodata, including index optimisation, tile preparation, cache management, and building structures to accelerate machine learning models (ML-ready datasets).

The activities of a digital surveyor also extend to the field of geospatial data security. Since geodesy operates with data containing information about critical infrastructure, engineering structures, transport systems, and sometimes even restricted data of defence significance, there is a need to integrate data protection mechanisms in accordance with the international recommendations of the OGC Security Working Group and the security requirements formulated within the framework of the European Copernicus programme. In this context, digital surveyors participate in the implementation of access control policies, the construction of authorisation models, the determination of information sensitivity levels, and the implementation of anonymisation and geospatial generalisation mechanisms for open data sets. This level of competence was previously only characteristic of IT specialists, but the modern integration of GIS and artificial intelligence makes it an important component of the professional activities of a geodesist.

A significant part of a digital surveyor's work involves modelling uncertainty and assessing the risks of geospatial decisions. Modern intelligent systems allow errors to be assessed not only at the level of individual measurements, but also at the level of complex spatial models. For example, when creating a digital terrain model based on LiDAR data, models assess the probabilistic characteristics of errors depending on the type of surface, building density or vegetation cover density. In urban development analytical tasks, digital surveyors use statistical modelling methods, Bayesian graph models and ensemble forecasting methods to assess the impact of uncertainty on planning decisions and the accuracy of cadastral or urban planning calculations. This provides a scientifically sound basis for management decisions at the local government level.

The ability of digital surveyors to work with large volumes of unstructured data is also becoming increasingly important. Information flows from 3D scanners, mobile mapping systems, SAR satellites, and high-resolution aerial photography systems

require specialised methods of pre-structuring and distributed processing. In this regard, digital surveyors use automatic classification tools, dimensionality reduction algorithms (PCA, t-SNE, UMAP), anomaly detection methods (Isolation Forest, LOF, Autoencoders) and GPU/TPU-accelerated computing systems. Such tools create conditions for the application of intelligent models in real or near real time, which is extremely important for operational monitoring and response to hazardous processes.

The transformation of professional competencies required of a digital surveyor deserves special attention. In addition to classical knowledge of geodesy, cartography and geoinformatics, a modern specialist must have programming skills, be able to work with cloud service APIs, understand the principles of neural network construction, know signal processing methods and have data pipeline construction skills. Another important component is the ability to audit artificial intelligence models, analyse accuracy metrics, control the retraining process, manage versions of geodata and algorithms, and document models in accordance with ML governance requirements. This set of competencies forms the basis of the profession of the future, which has become central to most organisations where geospatial data is a critical resource.

In fact, the digital surveyor is a catalyst for innovation in the field of territorial management. They not only ensure the technical accuracy of cartographic products, but also create conditions for the development of new intelligent services — from automated urban planning decision-making systems to digital environmental risk monitoring platforms. Modern communities that implement such systems gain competitive advantages in spatial planning, resource management, development strategy formulation, and emergency response. Therefore, the role of digital surveyors will only grow in the coming decade, and the requirements for their competencies will become more complex, anticipating market needs and forming the foundation for the digital transformation of the geospatial industry.

3.9   Intelligent methods for constructing digital twins of territories based on geodetic and geospatial data

The development of the concept of digital twins is one of the key trends in modern geoinformation science, integrated with artificial intelligence technologies. In geodesy and land management, a digital twin is interpreted as a comprehensive dynamic model of a physical object or territorial system, formed on the basis of geodetic measurements, satellite observations, remote sensing data, a network of sensors, and analytical algorithms, including machine learning methods. An intelligent digital twin is capable not only of reproducing the geospatial structure of a territory, but also of predicting its changes, assessing risks, modeling development scenarios, and providing support for management decisions. In recent years, scientific research has increasingly viewed digital twins as a key component of municipal GIS and Smart City platforms [107].

Creating a digital twin of a territory is impossible without high-quality geodetic and geospatial data. The first step is to build a basic three-dimensional model of the terrain based on GNSS measurements, tacheometric surveys, laser scanning, and orthophoto plans. At the same time, neural networks significantly improve the quality of raw data processing: convolutional networks allow noise and artifacts to be removed from laser point clouds, depth segmentation algorithms simplify object classification, and super-resolution models improve the detail of satellite images, which is especially important for urban areas. For example, the ESRGAN method makes it possible to increase the informativeness of Sentinel-2 optical data by increasing their resolution to a level sufficient for modeling small buildings [108].

The intellectual component of a digital twin manifests itself in the model's ability to self-update and self-correct. It is important to use machine learning algorithms capable of synthesizing new information based on input data streams. An example is the use of LSTM-type recurrent networks to assess relief changes based on InSAR data, which allows predicting slow vertical displacements of the Earth's surface characteristic of landslide areas or technologically loaded territories [109].

The detail of the digital twin is significantly increased by the integration of LiDAR data. Laser scanning allows you to create highly accurate 3D models of objects, but it is intelligent algorithms that ensure the correct classification of billions of points. PointNet and PointCNN algorithms allow automatic differentiation between the classes "land," "vegetation," "buildings," "engineering networks," and "small architectural forms" with an accuracy of over 90%. This makes it possible to create a digital twin with sufficient detail for engineering planning, deformation monitoring, and building control. In urban planning, this paves the way for automatic verification of the compliance of construction objects with project data, as well as for modeling shadow casts or insolation of neighborhoods.

An important aspect is the integration of Internet of Things (IoT) sensor networks, which provide a constant flow of data on the state of infrastructure, environmental parameters, and fluid processes. Artificial intelligence allows for filtering, aggregation, and anomaly detection based on this data, turning the digital twin into an operational monitoring tool. In EU cities, such systems are used to detect accidents on heating networks, predict traffic flows, and control air quality. Machine learning models such as Gradient Boosting or Random Forest allow analyzing the relationships between environmental parameters and predicting possible risk impacts.

The creation of digital twins of territories is impossible without the development of intelligent scenario analysis modules. Neural network simulation models are used to predict changes in landscape and ecological systems, traffic flows, and the development of engineering networks. In the context of territorial communities, this allows for predicting the consequences of construction, changes in groundwater levels, risks of flooding or subsidence of structures, and optimizing energy supply schemes. Thanks to the use of deep learning models, the digital twin functions not only as a visual tool but also as a full-fledged decision support system. The use of Transformer architectures, which have proven themselves in spatio-temporal forecasts of ecosystems and urban dynamics, is extremely relevant [110].

In municipal management practice, digital twins are becoming the foundation for creating intelligent geoinformation platforms for "smart cities," which allow for

real-time reproduction of the territory's structure and modeling of development options. Systems such as Urban Digital Twin, which are being actively implemented in Singapore, Helsinki, and Rotterdam, combine machine learning models, sensor networks, and comprehensive GIS applications to optimize development, manage infrastructure, and reduce environmental risks [111].

Thus, intelligent methods for constructing digital twins of territories are forming a new paradigm for managing spatial systems, in which geodetic data, artificial intelligence, GIS, and forecasting models function as a single complex. The development of these technologies determines the future of geoinformation systems and creates conditions for building highly accurate, adaptive, and self-learning models of territories that can provide effective support for management decisions at the level of local communities and large cities.

Another key aspect of the development of digital twins of territories is the use of cloud computing and high-performance computing (HPC) platforms. Processing geodetic measurements, multi-core LiDAR point clouds, or weekly time series of Sentinel-1/2 satellite data requires significant resources. Therefore, modern digital twins are implemented in formats compatible with distributed computing: Google Earth Engine, Microsoft Planetary Computer, Amazon Web Services, and separate national geocomputing clouds. These platforms ensure the prompt updating of models, allowing real-time recalculation of parameters such as relief, hydrology, insolation, or engineering load [46].

An important component of digital twin development is engineering infrastructure behavior models. Municipal GIS increasingly integrate models of pipelines, power grids, heating networks, drainage systems, and storm sewers. Thanks to the use of artificial intelligence methods, such models can automatically identify areas of potential accidents, assess the risk of pipe breaks, predict power grid overloads, and identify inefficient sections of engineering systems. For example, Graph Neural Networks (GNN) models are highly effective in predicting the status of network objects, as they allow for the analysis of complex spatial graphs of engineering networks and their interconnections [112].

Intelligent digital twins are also extremely effective in modeling natural risks. The use of deep neural networks and generative models allows not only to reproduce existing spatial processes, but also to generate their future scenarios. Models based on Variational Autoencoders (VAE) or Generative Adversarial Networks (GAN) are capable of creating simulations of floods, urban sprawl, soil degradation, or the spread of forest fires based on the analysis of long-term time series of remote sensing data. Such intelligent models make it possible to assess potential environmental threats many years in advance, forming the basis for risk-oriented spatial planning and the development of sustainable development strategies [113].

The concept of digital twins also involves the integration of behavioral models that describe human interaction with the territory. These include population mobility models, traffic load forecasts, and models of interaction between types of buildings and social infrastructure. Machine learning algorithms analyze massive amounts of data from mobile operators, Wi-Fi tracking, telematic sensors, and video surveillance cameras, allowing for the creation of accurate models of residents' movements. In particular, Transformers-based models are successfully used to forecast traffic flows in complex urban networks with tens of millions of observations per day [114].

Intelligent digital twins also serve as a platform for testing urban planning and environmental solutions without the need to make changes to the real environment. Simulation models allow analyzing the consequences of changes in building density, street reconstruction, optimization of green areas, or development of the transport network. Deep neural networks can be used to simulate the distribution of air pollutants, acoustic noise, and changes in the microclimate within neighborhoods, which is particularly important for the development of sustainable and comfortable urban spaces. In many cities in Europe and Asia, digital twins are used to assess the insolation of new buildings, predict wind corridors, and determine the level of heat load during hot periods.

An essential element in the development of digital twins of territories is the standardization of data formats and interoperability. International standards ISO 191xx, INSPIRE Directive, and OGC (Open Geospatial Consortium) documents define

requirements for structure, accuracy, metadata, exchange interfaces, and web services. Intelligent digital twins must comply with these standards, which ensures integration with external spatial data sources and long-term system compatibility. Today, the most promising concept is GeoAI interoperability — standardized interaction between GIS and artificial intelligence modules, which allows the creation of open, scalable, and modular digital twins. Particular attention should be paid to the accuracy and quality control of digital twins. Intelligent models automatically assess data uncertainty, predict possible errors, and use Bayesian estimation methods to determine confidence intervals for resulting maps and models. Thanks to uncertainty quantification methods, it is possible to accurately determine the degree of confidence in the predictions generated by a digital twin. This is critical for risk-oriented territory management, particularly in the areas of engineering safety and environmental monitoring [115].

Thus, digital twins of territories created using intelligent methods of processing geodetic and geospatial data are a fundamentally new tool in the system of municipal management, spatial planning, and engineering analysis. They combine the accuracy of classical geodetic measurements with the capabilities of modern neural networks, ensuring the efficiency, accuracy, and adaptability of management decisions. The formation of digital twins is becoming the foundation of the concept of a "digital territory," within which all development, planning, and monitoring processes can be carried out with a fundamentally new level of intellectual support.

An important component of intelligent digital twins of territories is the modeling of the temporal evolution of spatial systems. Modern geoinformation models are increasingly moving from static representations of territory to dynamic spatio-temporal models that allow for the analysis of changes not only in space but also in time. Such models are formed on the basis of time series of satellite observations, periodic GNSS measurements, regular laser scanning, and data from IoT sensors that track the state of engineering infrastructure or natural processes. The use of recurrent neural networks, in particular LSTM and GRU, significantly improves the accuracy of forecasting complex processes—vertical shifts in the Earth's surface, traffic flows, changes in vegetation, water levels in water bodies, and smoke trails from industrial enterprises.

In many cities, LSTM models allow for the prediction of flooding in individual neighborhoods, taking into account both historical data and information obtained in real time [116].

A key feature of modern digital twins is the use of multi-sensor data integration based on machine learning methods. This allows information from various sources to be combined, including optical satellite images, Sentinel-1 radar data, laser point clouds, GNSS RTK data, tacheometric measurements, photogrammetric models from UAVs, temperature and humidity sensors, GSM data, and Wi-Fi analytics. Such data fusion requires the use of deep fusion models, which allow combining different spatial and temporal resolutions. Neural network-based fusing-and-stacking procedures ensure optimal source alignment, noise minimization, and reconstruction of missing values. The use of Multi-Modal Transformers models enables simultaneous processing of optical, radar, LiDAR, and vector data, which significantly improves the accuracy of territory modeling [88].

Researchers pay considerable attention to the issue of bias in digital twins. Since models are trained on historical data, they can inherit implicit systemic errors related to seasonality, uneven data collection, different sensor characteristics, or incorrect ground truth values. In response to this, intelligent debiasing methods are being developed—algorithms that automatically identify and compensate for systematic errors. These methods are based on Bayesian networks, probabilistic graph models, Gaussian processes, and Bayesian neural networks, which allow for the assessment of forecast uncertainty. This makes the digital twin more resistant to incorrect input data and increases its viability in complex urban environments.

Moving on to spatial risk modeling in digital twins, it should be noted that methods for intelligent assessment of man-made and natural hazards are of particular importance. Machine learning algorithms analyze structural features of the terrain, geological parameters, hydrogeological conditions, infrastructure loads, and climatic factors to form comprehensive risk maps. Such models are widely used in the EU to support the implementation of the EU Disaster Risk Reduction Framework. Recent

scientific studies demonstrate the high effectiveness of CNN models for spatial forecasting of landslides, erosion, flooding, and river channel changes [117].

Modern digital twins of territories also integrate VR/AR technologies, which allow users to interact with the model in an immersive environment. The use of virtual reality makes it possible to simulate scenarios for the development of territories, optimize the placement of buildings, perform 3D analysis of visibility and insolation, and assess the impact of development on the environment. AR technologies make it easy to superimpose elements of a digital twin onto real terrain, which is useful during engineering surveys, field inspections, infrastructure monitoring, and public discussions of urban planning documentation.

One of the most important and rapidly developing areas is the automatic generation of recommendations by digital twins. This is a qualitatively new level of intelligent systems that goes beyond forecasting. Based on the results of the analysis, the digital twin is able to offer engineering solutions, determine which areas of the territory require priority monitoring, and form recommendations for network reconstruction, transport management, optimization of development, or preservation of ecological balance. To do this, reinforcement learning (RL) models are used, which learn on the basis of rewards/penalties, gradually optimizing territory management strategies. In the US and Singapore, RL algorithms are successfully used to optimize urban traffic, manage energy and water resources, and prevent accidents in utility networks [118].

The potential for fully automated updating of digital twins should be emphasized separately. The use of deep models such as Self-Supervised Learning makes it possible to automatically update data structures, detect the appearance of new objects, and record the destruction, dismantling, or reconstruction of urban infrastructure elements without operator intervention. Such models learn from their own predictions, combining data from various sensors, and can provide model updates every 10–60 minutes, depending on the frequency of data reception.

Another promising area is the use of digital twins to model socio-economic processes. Spatial models allow us to predict the development of the real estate market,

assess the investment attractiveness of territories, and analyze migration trends and their impact on infrastructure. Intelligent models combine spatial data with econometric models, creating a new level of integration and allowing the effects of development, reconstruction, or zoning changes to be assessed based on real data.

Thus, the digital twin of a territory ceases to be just an accurate 3D model of the terrain. It becomes a full-fledged intelligent platform capable of collecting, analyzing, and interpreting geodata, predicting risks, optimizing spatial solutions, automatically responding to changes, and proposing options for engineering and management actions. Intelligent digital twins are becoming a central element of modern territory management systems, setting the standards for the 21st century in geodesy, geoinformatics, and municipal management.

3.10 Intelligent methods for analyzing and modeling Earth surface deformations based on GNSS, InSAR, and LiDAR data

Modeling of Earth surface deformations is one of the key tasks of modern geodesy, engineering monitoring, and spatial analysis. The development of artificial intelligence methods opens up new opportunities for the integrated processing of GNSS measurements, synthetic aperture interferometry (InSAR), and laser scanning (LiDAR), allowing for a detailed picture of surface displacements, predicting their development, and identifying potentially dangerous areas. Intelligent models can detect even minimal deformations with millimeter accuracy and perform scenario analysis to assess risks in built-up areas, infrastructure corridors, mining areas, and naturally hazardous areas.

GNSS technologies provide continuous time monitoring of points, allowing the detection of slow and fast vertical and horizontal displacements. However, classical methods of GNSS data processing do not always allow for high-quality filtering of noise, seasonal trends, or non-stationary changes. Therefore, in the last decade, machine learning algorithms have been actively introduced into monitoring practices, in particular, recurrent neural networks (LSTM), ensemble regression methods, and

Bayesian models, which allow predicting long-term changes in coordinates and assessing the uncertainty of results. The use of LSTM models significantly improves the accuracy of forecasting seasonality and hidden cyclical components in GNSS time series [119].

Among remote sensing methods, SAR interferometry (InSAR) deserves special attention, as it allows assessing ground surface deformations over areas of hundreds of square kilometers with an accuracy of several millimeters. Sentinel-1, ALOS PALSAR, and TerraSAR-X data make it possible to form dense displacement fields, but the InSAR signal is sensitive to atmospheric interference, moisture, vegetation, multipath, and signal decorrelation. Artificial intelligence significantly improves the quality of interferometric information through the use of convolution neural network-based filtering, automatic detection of incorrect interferograms, reconstruction of phase values, and construction of time series using the Persistent Scatterer Interferometry (PSI) method with optimization algorithms. In modern research, CNN models have become the standard for phase denoising and atmospheric component compensation [120].

LiDAR scanning—ground-based, aerial, or mobile—plays a critical role in creating a highly accurate digital model of terrain and deformable objects. Intelligent methods enable automatic classification of point clouds (ground/non-ground), detection of local changes between successive scans, segmentation of objects, and identification of structural deformations in buildings, bridges, dams, or industrial facilities. PointNet++ and KPConv models allow you to segment billions of points and find millimeter changes in the shape of structures, which is not possible with traditional point cloud comparison methods [99].

The combination of GNSS, InSAR, and LiDAR data forms an integrated approach to deformation analysis. Modern GeoAI models enable spatiotemporal data fusion by combining GNSS point measurements with large-scale InSAR fields and high-detail LiDAR models. Multi-modal deep learning algorithms automatically reconcile different types of data, align coordinate systems, compensate for noise, reconstruct gaps, and generate a unified deformation map. For example, dual-stream

networks allow simultaneous processing of radar and laser data, forming more accurate models of ground movements than each method separately.

Deformation prediction models also play an important role. The use of GRU, Temporal Convolutional Networks (TCN), and hybrid LSTM–CNN models allows for the reproduction of nonlinear patterns of ground surface movements, taking into account seasonality, atmospheric influences, industrial loads, and anthropogenic factors. In mining areas, deep models can predict soil subsidence rates and potential deformation zones several months before they occur. This reduces the risk of infrastructure damage and allows engineering measures to be taken in advance.

The use of artificial intelligence significantly improves the accuracy of detecting microdeformations, which are precursors to major deformation events. Anomaly detection methods — autoencoders, isolation forests, One-Class SVM — automatically identify changes that fall outside normal trends, which is particularly useful for monitoring dams, tunnels, overpasses, and bridges. Such algorithms act as early warning systems, minimizing the risk of catastrophic damage.

Modern digital twins of deformations also allow geological, hydrological, construction, and loading parameters to be integrated into modeling. By combining physical models (finite element modeling) with intelligent approaches (Physics-Informed Neural Networks — PINN), it is possible to simulate complex processes such as ground subsidence, slope failure, or the behavior of engineering structures under load. PINN models allow simultaneous consideration of field measurements, geology, and physical parameters of the environment, which makes the modeling results significantly more accurate than classical analytical methods.

Thus, the integration of GNSS, InSAR, and LiDAR data, combined with modern intelligent algorithms, allows for the construction of a comprehensive, highly accurate, and adaptive system for monitoring deformations of the Earth's surface. Such a system provides the ability to quickly identify dangerous trends, create scenarios for the development of processes, and form a system for early response to natural and man-made threats. Intelligent approaches are ushering in a new era in geodesy and engineering geodynamics, allowing a transition from traditional post-factum

diagnostics to predictive, analytical, and preventive management of territories and objects.

One of the critically important aspects of intelligent deformation analysis is the formation of a unified coordinate system for the integration of GNSS, InSAR, and LiDAR data. Since GNSS measures changes in the global geocentric system, InSAR provides displacement in the line of sight, and LiDAR operates in local systems, there is a need for intelligent transformation algorithms that allow all data to be combined into a single three-dimensional field. Modern approaches use neural networks to automatically estimate transformation parameters between coordinate systems, including affine and deformable transformations, which significantly reduces the amount of manual work and eliminates systematic transformation errors. Today, Spatial Transformer Networks models are actively used, which dynamically adapt the geometry of data during training, ensuring high-precision spatial coordination of heterogeneous measurements.

An important component of automated monitoring is the construction of multi-level analysis models. At the first level, preliminary filtering of data is performed — GNSS time series, interferograms, or point clouds. At the second level, machine learning-based deformation detection models are applied. At the third level, forecasting, trend detection, and risk zone clustering take place. This multi-stage pipeline increases the reliability of results and allows algorithms to work in real time, adapting to updated data. The multi-stage approach is widely used in geodynamic studies in the US, Japan, the Netherlands, and Norway, including monitoring earthquakes, subsidence, tectonic shifts, and industrial deformations [122].

Modeling deformations in areas with man-made loads requires special attention—for example, in areas of mineral extraction, along transport corridors, in places where oil and gas wells, pits, and engineering structures are operated. Intelligent algorithms allow distinguishing between components of ground surface movement caused by tectonic, hydrological, or man-made processes. To do this, approaches based on Blind Source Separation are used, as well as decomposition learning methods, where the model itself separates the total signal into physically determined

components. For example, in mining areas, such models allow the separation of subsidence caused by groundwater pumping from subsidence caused by mine development. This significantly improves the accuracy of risk assessment for buildings and critical infrastructure.

At the current stage of geodesy development, an important task is to create models that are resistant to unstable external conditions. GNSS data are subject to multipath effects; SAR images are affected by atmospheric phase; LiDAR scanning depends on weather conditions and vegetation density. The use of intelligent models with a self-correction function allows maintaining the stability of analysis even in the presence of data errors. Autoencoders and feedback networks are used to reconstruct missing values, while generative models compensate for signal loss. Variational Autoencoders and Diffusion Models are particularly effective, allowing the restoration of interferograms where the phase is lost over large areas — something that was previously considered impossible or economically unfeasible to calculate.

One of the revolutionary areas is Physics-Informed AI — models that combine physical equations of the deformation process with deep learning. Such models incorporate the laws of elasticity, mechanics of continuous media, hydrogeological parameters, and patterns of subsidence of structural arrays. PINN models (Physics-Informed Neural Networks) are capable of simultaneously taking into account deep rock stresses, groundwater levels, deformation modules, and InSAR/GNSS data to create physically sound predictions. Compared to purely statistical methods, PINNs demonstrate significantly higher accuracy over long forecast horizons, making them particularly effective for predicting land subsidence and landslide processes [123].

An important area of development is the creation of panoramic deformation models that combine all available sensor sources into a single system. Such models allow:

- performing 3D vectorization of deformations;
- determine vertical and horizontal components of movement;
- interpolate displacement fields between point and plane sources;
- generate risk maps and stress diagrams;

- analyze cause-and-effect relationships of deformation processes.

The most accurate models are those that use Graph Convolutional Networks (GCN), which allow deformation processes to be analyzed as a graph network, where each GNSS point / InSAR pixel / LiDAR cluster acts as a graph node. This makes it possible to identify spatial dependencies that previously went unnoticed.

GCN models allow you to:

- automatically determine the centers of deformation activity,

- classify types of deformations (subsidence, uplift, landslides),

- determine the areas of influence of engineering structures.

In urban planning, such models form the basis for monitoring multi-story buildings, controlling the condition of subways, bridges, and transport tunnels.

Early warning algorithms play a special role in practical applications. Intelligent systems analyze time series in real time and identify dangerous deviations from the forecast model. Algorithms such as Prophet Neural, LSTM-AutoRegressive, and Temporal Fusion Transformers allow you to estimate the probability of a sudden change in deformations 1–7 days before the event. This is critically important in areas where even small displacements can cause building destruction or network failures.

The assessment of forecast uncertainty, which is a mandatory element of international deformation models, is of particular importance. Bayesian neural networks allow generating forecasts with confidence intervals, and Dropout-as-Bayesian models increase the stability of estimates. This allows deformation maps to be constructed not only in the form of "hard" values, but also in the form of a risk field, which significantly increases the value of the digital twin of the territory.

Such approaches form the basis of modern deformation monitoring systems in the EU, the US, China, and Australia, where intelligent models are integrated with automated observation platforms. In Ukraine, such technologies are particularly relevant due to the need to assess man-made and post-war deformation activity, in particular subsidence in areas of destruction, deformation of engineering structures, and monitoring of natural slopes.

Intelligent analysis of ground surface deformations is impossible without assessing the temporal stability of the signal and separating short-term fluctuations from long-term trends. This is especially relevant in regions with complex soil structures, active anthropogenic activity, or significant seasonal influence of groundwater. The most effective approach for such cases is to combine Seasonal-Trend decomposition (STL) methods with Temporal Fusion Transformers (TFT) neural networks, which allow the formation of hybrid time series models. Such models take into account seasonality, trends, short sharp changes, and noise components, forming a more accurate interpretation of GNSS and InSAR data than classical analytical methods [124].

An important intellectual tool in deformation modeling is spatio-temporal clustering, which allows grouping areas of territory according to the similarity of deformation process behavior. For example, ST-DBSCAN and HDBSCAN algorithms can identify clusters characterized by common movement patterns, such as:

- stable areas without deformations;

- areas of gradual subsidence;

- areas with periodic uplifts and subsidence;

- areas with high instability preceding destruction.

Intelligent clustering models not only automatically identify such groups, but also determine the degree of risk, the nature of movement, and potential drivers of deformation—for example, man-made influences, changes in groundwater levels, vibration loads, soil waterlogging, etc. This is extremely useful for predicting accidents in residential buildings and monitoring excavations, bridges, dams, and other critical structures.

Recent studies also show the high effectiveness of spectral analysis and wavelet transform methods for detecting hidden cyclic components of deformation processes. For example, periodic seasonal subsidence may be associated with groundwater fluctuations, freeze-thaw cycles, or changes in building loads. Wavelet analysis allows for extremely accurate localization of such cycles in time, and hybrid neural networks

combine their information with InSAR and GNSS data to create multi-component models for detailed forecasting.

Of particular value in modern deformation analysis are causal models, which allow not only to determine the fact of displacement, but also to establish its causes. For example:

- selective soil collapse can be caused by water leakage;

- local surface uplift can be caused by underground gas movements;

- acceleration of deformations can be caused by man-made soil erosion or vibrations.

Models such as Granger Causality, Bayesian Structural Time Series, and Neural Causal Discovery allow integrating geodetic data with environmental parameters (precipitation, temperature, engineering loads), enabling physically sound conclusions to be drawn about the causes of deformation. In combination with PINN models, such approaches form a completely new class of predictive-causal digital twins that not only reflect actual changes but also explain their origin.

Separately, it is important to highlight the issue of intellectual interpolation and data reconstruction, which are critically important for the Ukrainian context, where some data may be lost due to hostilities, infrastructure destruction, or the interruption of observation stations. U-Net, Autoencoder, and Diffusion Models neural networks allow for the reconstruction of incomplete interferograms, the restoration of missing GNSS lines, and the reproduction of fragments of LiDAR point clouds. This makes it possible to create deformation maps even under conditions of incomplete information.

The most conservative monitoring systems are already actively integrating intelligent models of automatic quality control. The use of ISO 19157 (Quality of Geographic Data) in combination with AI modules allows you to:

- detect false measurements;

- mark suspicious data;

- update metadata;

- ensure the informational transparency of digital twins;

- automatically assess data reliability.

Modern deformation monitoring systems are moving towards the concept of a comprehensive intelligent profile of an object, where a multidimensional vector of parameters is formed for each building, site, or engineering object, including:

- the speed of vertical and horizontal displacements;

- trend variability;

- risk indices;

- foundation stability;

- response to external loads;

- potential accident forecast.

The use of ensemble models (XGBoost, LightGBM, CatBoost) allows sites to be ranked according to risk level and priority lists to be formed for engineering surveys.

Intelligent visualization of deformation analysis results requires separate consideration. Modern GIS platforms allow the integration of:

- thermal risk maps,

- 3D vector displacement fields,

- deformation trajectories,

- multi-layer risk models,

- temporal animations of deformation processes.

The use of graphics engines such as CesiumJS, Unreal Engine, and Unity allows the creation of realistic 3D models with integrated deformation fields, which is becoming an important tool for urban planners, surveyors, and engineers.

Thanks to the development of AI technologies, it is now possible to build fully autonomous deformation monitoring systems that include:

- automatic data reading from sensors, satellites, and scanners;

- intelligent data filtering and reconciliation;

- construction of spatio-temporal deformation models;

- classification and clustering of deformation processes;

- identification of automatic hazard triggers;

- generation of forecasts and recommendations;

- updating of digital twins in online learning mode.

Such systems are already in use in Japan, Singapore, Iceland, and Italy, demonstrating exceptional effectiveness in disaster prevention and monitoring of complex territories.

3.11   Intelligent models for anomaly detection and diagnosis of geodynamic processes in geodetic data

Intelligent methods of analyzing geodetic and geospatial data open up fundamentally new approaches to detecting anomalies that signal the development of potentially dangerous geodynamic processes. Unlike traditional statistical criteria—such as the three-sigma rule, the Grubbs criterion, or autocorrelation analysis, modern machine learning models allow the detection of complex, multidimensional, and nonlinear patterns characteristic of earth surface shifts, man-made subsidence, accelerated deformations, and changes associated with seismic and hydrogeological processes. The high sensitivity of intelligent models to data structures significantly improves the capabilities of operational diagnostics of the condition of territories and infrastructure objects, especially in rapidly changing conditions.

The leading direction of development is the application of deep models for detecting anomalies in GNSS time series, where recurrent networks (LSTM, GRU), autoencoders, and hybrid models with a self-attention mechanism are most effective. LSTM networks are capable of analyzing subtle changes in the rhythmic structure of deformations, detecting slow processes that do not have a pronounced amplitude but may be precursors to sudden deformation shifts. Autoencoders, on the other hand, learn to reproduce the "normal" state of a time series, and any difference between the input and reconstructed sequences signals an anomaly. This approach has proven effective in vertical displacement monitoring systems, where deviations of 2–3 mm can be critically important [125].

In the case of interferometric SAR data, the problem of anomalies is much more complex, since a single image or interferogram can contain thousands of local artifacts caused by atmospheric phase, coherence losses, geometric distortions, vegetation

cover, and other external factors. For such tasks, spatio-temporal models are used, which analyze spatially related blocks rather than individual pixels. Models such as Convolutional LSTM or ConvGRU function as spatio-temporal filters, allowing noise components to be separated from stable deformation patterns. 3D-CNN models are particularly effective, analyzing the interferogram stack as a three-dimensional data array, which improves the accuracy of anomaly detection in urban areas or densely built-up areas [109].

Equally important is the application of intelligent models to LiDAR data, where anomalies can be changes in the elevation structure of the terrain, deformations of engineering structures, distortions of slope surfaces, or local landslides. In such cases, deep models analyze not time series, but changes in the geometry of point clouds. The most effective approaches are PointNet++ and graph neural networks (GCN), which are capable of detecting structural deformations at the level of individual surface segments. Graph models allow analyzing local topological anomalies — for example, an increase in surface curvature, changes in slope inclination, deformation of bridge support structures. It is particularly important that GCN models are capable of working with unevenly distributed LiDAR points, which is characteristic of scans performed in difficult conditions [121].

In geodynamics, intelligent models allow the construction of multi-component diagnostic systems that simultaneously analyze GNSS, InSAR, LiDAR, geological maps, data on precipitation, temperature, groundwater, and loads on structures. In such systems, an anomaly is defined not only as a deviation from the statistical norm, but also as a violation of the cause-and-effect structure of the data. For example, a sharp vertical displacement with a stable groundwater level may indicate a man-made factor, while cyclical changes may indicate natural seasonal phenomena. To do this, Granger Causality, Structural Equation Models, and Neural Causal Discovery models are used to identify the real drivers of deformation.

Early warning models, which operate in real time, occupy a special place in the diagnosis of geodynamic processes. Such models analyze time series using LSTM or Transformer architectures and identify critical changes in trends that precede rapid

deformations or structural failures. The combination of neural networks and probabilistic models allows forecasts to be made with confidence intervals, which is important for decision-making in engineering monitoring [87].

Modern approaches involve the creation of anomaly maps (Anomaly Atlas), in which each fragment of the territory is characterized by a spectrum of typical and atypical processes. For each site, a vector of features is formed, which includes deformation rates, variability, seasonality, local geometry, signal intensity, and other characteristics. Clustering such vectors (t-SNE, UMAP, HDBSCAN) allows typical deformation processes to be separated from atypical ones, as well as grouping anomalies that are similar in structure. This approach is widely used in Italy, Iceland, and Japan to monitor volcanic, seismic, and man-made deformations.

An important addition to the intelligent analysis of anomalies is the assessment of uncertainty, which allows determining the degree of confidence in each result. Bayesian neural networks, Dropout inference, and Ensemble Learning allow forming uncertainty intervals and identifying areas where the model works less stably. This is especially relevant in areas with complex topography or low signal coherence.

Systems of this type are gradually forming the basis of digital twins of geodynamic processes, which combine all data sources, intelligent analysis methods, and forecasting mechanisms. A digital twin not only detects anomalies, but also models their development, identifies probable scenarios for changes in the state of the territory, and automatically generates recommendations for engineers, local authorities, and safety specialists.

Another important direction in the development of intelligent anomaly detection systems is the introduction of hybrid models of spatio-temporal analysis, which simultaneously take into account the local context, temporal sequence, and structural relationships between objects. Current research shows that combining graph neural networks (GNN) with Transformer models allows not only for the detection of individual anomalies, but also for the recognition of patterns of abnormal phenomena in geodynamic systems. For example, in areas prone to landslides, such models can determine the spatial distribution of unstable zones and predict the possible trajectory

of displacement — this significantly exceeds the capabilities of classical methods of interpolation and statistical processing of GNSS or InSAR data [128].

In large urban areas, the task of detecting anomalies is complicated by numerous sources of noise—transport vibrations, thermal effects from buildings, man-made loads, and changes in soil moisture. Therefore, there is a growing trend toward the implementation of multisensory neural models that combine GNSS, SAR, LiDAR, IoT sensors, seismic stations, and meteorological information in a single intelligent environment. Such models allow the creation of comprehensive anomaly profiles that include geometric, temporal, spectral, and causal features. For example, combining microseismic data with InSAR allows the diagnosis of early phases of landslides when changes are not yet visible in the optical or LiDAR range [159].

In deformation analysis systems, an important task is to identify anomalies such as "foreground events," where short-term but intense changes mask long-term trends. For example, isolated impulsive changes in groundwater levels can cause temporary subsidence, which is mistakenly perceived as the beginning of a dangerous process. To recognize them, Bayesian Change Point Detection, VAE-based anomaly segmentation, and Gaussian Processes models with kernel structures that take seasonality into account are used. This makes it possible to identify real structural changes in the behavior of the territory and not confuse them with short-term noise influences.

The development of geodynamic monitoring systems stimulates the emergence of intelligent stability maps, in which each territory is characterized by indicators of:

- local deformation activity;

- accuracy of GNSS/SAR measurements;

- stability of trends;

- degree of correlation with natural factors;

- presence of anomalous events in the past;

- temporal predictability of models.

Such maps can be automatically updated using online learning algorithms that adapt the model as new data becomes available. In this context, Meta-Learning

methods are particularly effective, as they allow the model to quickly adapt to new types of deformation processes in different geological or urban conditions.

Intelligent anomaly simulation models are increasingly being used in the diagnosis of geodynamic processes. These models generate synthetic deformation signals, allowing the quality of the system to be tested without risk to real territories. Generative Adversarial Networks, Diffusion Models, and Variational Autoencoders allow the creation of realistic sets of "anomalies," which include:

- sudden vertical subsidence;

- gradual horizontal shifts;

- combined X/Y/Z axis displacements;

- complex deformations with nonlinear dynamics.

This synthetic data allows testing, calibrating, and improving intelligent algorithms, increasing the stability of the system even in unlikely scenarios.

An important problem for monitoring is the complex interaction of several deformation processes, such as simultaneous subsidence due to water pumping and horizontal displacement due to slope instability. Intelligent decomposition learning models allow the total deformation to be divided into independent components, which significantly improves the accuracy of assessing individual physical processes. They are widely used in mining, engineering geology, and monitoring of megacities (Tokyo, Seoul, Milan).

Recent studies show that the greatest effect in diagnosing anomalies is achieved by combining indicator signs, including:

- the difference between predicted and actual displacements;

- deviation in the time rate of deformation;

- changes in the local geometry of the point cloud;

- increase in signal entropy;

- shifts in spectral characteristics;

- disruption of topological connections between points in the local graph.

Such features are used both in classical algorithms (Isolation Forest, One-Class SVM) and in deep neural network models, which allows to increase the accuracy of diagnostics and reduce the level of false positives.

The implementation of intelligent models has resulted in the creation of comprehensive geodynamic process diagnostic systems capable of:

- automatically detecting anomalies in GNSS/InSAR/LiDAR data;

- determining the type and nature of the anomaly;

- assess the probability of dangerous developments;

- create a digital twin of the territory's dynamics;

- generate recommendations and warnings.

Such systems are critically important for Ukraine, where a significant part of the territory has been affected by man-made and military influences, increasing the risk of deformation, subsidence, erosion, and destruction of infrastructure.

3.12 Intelligent systems for automated classification and vectorization of geodetic and cartographic data

Modern intelligent methods of processing geodetic and cartographic data increasingly rely on deep learning algorithms that enable automated classification, segmentation, and vectorization of objects based on satellite images, orthophoto plans, laser scanning materials, and traditional topographic maps. The integration of artificial intelligence into vectorization processes significantly reduces office processing time, increases accuracy, and ensures scalability regardless of the study area. Such systems are becoming a key element in the formation of digital twins of territories, geodata for GIS, as well as cadastral and urban planning registers [129].

Today, automated classification of geospatial data is mostly based on deep convolutional neural networks (CNN), segmentation architectures such as U-Net, DeepLabv3+, HRNet, as well as transformer models (SegFormer, Swin-Transformer), which allow analyzing complex spatial patterns. They are used to automatically extract linear (roads, networks), polygonal (building contours, fields, water bodies), and point

objects (supports, hydraulic structures) in multispectral and radar images. In the case of geodetic data, these models are capable of recognizing the boundaries of relief forms, elements of engineering networks, man-made objects, and structural lines of the earth's surface.

Automated vectorization of topographic plans and maps is particularly important, where classical methods (semi-manual tracing, threshold segmentation, polygonization) often do not provide sufficient accuracy. In contrast, neural network-based systems allow instant separation of different types of objects, even if they have low contrast, overlap, or noisy geometric contours. In this context, research by Microsoft AI for Earth (2021), Google DeepMind (2023), and Maxar GEOINT (2022) show that neural network approaches provide 25–60% higher accuracy in building contour recovery compared to traditional Sobel/Canny algorithms, active contours, or k-means clustering.

Semantic segmentation methods occupy a special place in intellectual processing, allowing not only to identify objects, but also to classify them according to their content. For example, in an urban environment, such models are capable of automatically determining categories of development (residential, industrial, administrative), types of road surfaces, landscaping, and elements of engineering infrastructure. In geodesy, this means the ability to automatically fill GIS base layers, create topologically correct models, and form cadastral vectors based on images without operator intervention [130].

An equally important component is the vectorization of laser scanning materials, where the output data is represented by a point cloud containing information about coordinates, reflection intensity, and spectral characteristics. Intelligent algorithms, such as PointNet, PointNet++, and RandLA-Net, allow each point in the cloud to be classified and automatically generate vector models of buildings, terrain, and other objects, which can then be imported into CAD and GIS. This opens up opportunities for the automatic generation of 3D models, reconstruction of engineering structures, modeling of high-rise buildings, and monitoring of deformation dynamics.

Hybrid approaches that combine classical image analysis algorithms (thresholding, morphological filtering, region-growing) with deep neural networks are increasingly being used in the vectorization and classification process. This approach is

particularly effective when working with historical maps, scans of technical plans, drawings, or cadastral documentation, where there is noise, printing defects, paper deformation, or overlapping symbols. Cartographic OCR systems play an important role in this process, allowing for the automatic recognition of symbols, text captions, elevation indices, and other elements of cartographic content.

An important trend is the development of intelligent CAD vectorizers that allow raster drawings to be converted into full-fledged DXF/DWG models. Models based on transformers and CNN (e.g., Raster2CAD, DeepCAD, ClipCAD) can automatically recognize walls, axes, structural elements, and communications, form topologically correct DWG layers, and close polygonal structures. This allows you to significantly reduce the time required to digitize engineering documentation and minimize the human factor.

Today, intelligent vectorization systems are inextricably linked to the concept of explainable AI (XAI), which provides transparency and control over classification and segmentation models. The SHAP, Grad-CAM, and Integrated Gradients methods allow you to determine why a model assigns a particular pixel or point to a specific class. This is critically important for geodesy, where every decision has legal implications, particularly when forming the boundaries of land plots, real estate objects, or elements of engineering infrastructure.

The development of intelligent classification and vectorization methods is particularly evident in areas where the accuracy of spatial data determines the security of infrastructure, territorial development planning, and the formation of cadastral and urban planning registers. One of the most important areas is the automated vectorization of linear objects, in particular roads, sidewalks, utilities, sewerage and water supply networks. Deep learning-based algorithms such as Holistically-Nested Edge Detection (HED), LineNet, and the latest transformer architectures PolyWorld Transformer and DeepRoadMapper allow road routes to be reconstructed even in conditions of significant noise, shading, and partial overlap of objects in an urban environment. Practical results from Google Research (2022) show that such models can improve the accuracy of road network tracing by an average of 40–65% compared to classical morphological filtering.

In surveying practice, vectorization of linear objects is key to creating engineering models of underground infrastructure, where it is necessary to accurately identify the location of cable routes, pipelines, heating networks, and collectors. The use of deep learning models for analyzing ground-penetrating radar (GPR) data has been one of the breakthroughs in recent years. Neural network architectures such as GPRNet and SubterraAI Model allow automatic detection of underground anomalies, structures, and tunnels from radar images, which previously required highly skilled operators and lengthy interpretation.

Another key area is the automatic vectorization of polygonal objects, primarily urban development, building contours, structures, industrial facilities, and landscape elements. The Mask R-CNN, Cascade Mask R-CNN, U^2-Net, and Segment Anything Model (SAM) networks demonstrate excellent results in detecting building contours even in challenging conditions where shadows, seasonal changes, incomplete visibility, or spectral shifts are present. Of particular note is the combination of SAM with geodata ("GeoSAM"), which allows semantic information to be integrated into the segmentation process and vectorization to be performed with virtually no training—the model adapts to the image in real time. This opens up new opportunities for cadastral services and municipal GIS, where the speed of data updating is critical.

Intelligent systems are also actively developing in the field of automated recognition of topographic signatures, including OCR and OCSR (Optical Character and Symbol Recognition), which allows processing scanned topographic maps, technical documentation, field journals, and historical materials. Models that combine CNN and Transformer (e.g., TrOCR, LayoutLMv3, DocFormer) are capable of recognizing textures, elevation symbols, contour line indexing, isolines, hydrographic grids, and other cartographic symbols with high accuracy. This enables automated filling of geodatabases, reducing labor intensity by 5–10 times.

Vectorization of point clouds obtained from aerial and ground LiDAR scanning has now become the foundation for automated creation of 3D models of territories. With the help of PointNet and its modifications, each point is classified into the categories "land," "vegetation," "buildings," "linear structures," and "small architectural forms."

The result is a vectorized relief and three-dimensional models of cities that can be integrated into digital twins, BIM systems, and cadastral resources. Graph Neural Networks (GNN) models are particularly promising, as they take into account the spatial topology of points and allow for the vectorization of complex structures such as bridges, overpasses, tunnels, or multi-level engineering networks.

It is worth noting the development of approaches to generative reconstruction of geospatial objects using NeRF (Neural Radiance Fields) and 3D Gaussian Splatting models. These technologies allow highly accurate 3D models of urban areas to be constructed from multiple angles, which are automatically vectorized as geometric primitives suitable for GIS and CAD. Generative models not only reproduce the shape of an object, but are also capable of reconstructing inaccessible or partially closed areas, which is of great importance for monitoring destroyed territories in Ukraine.

Automated vectorization has also given impetus to the development of geospatial deduplication systems — the intelligent merging and harmonization of data sets from different sources. In the process of integrating data with different spectral resolution, temporal frequency, or geometric accuracy, AI-based models determine which objects match, which are duplicates, and which are unique. This has made it possible to quickly generate integrated maps, cadastres, and digital terrain models that combine GNSS, LiDAR, InSAR, aerial photography, and drone data.

In general, intelligent automated classification and vectorization systems are becoming a central element of modern geodesy and cartography. They significantly accelerate the process of creating digital terrain models, reduce the cost of field work, minimize the human factor, and ensure high accuracy in determining the geometric and semantic characteristics of objects. Against the backdrop of the development of digital twins of territories, Smart City concepts, and the digital transformation of spatial data, the role of such systems will only grow.

One of the most promising areas of development for intelligent classification and vectorization systems is the integration of deep learning models into automated office processing of geodetic materials. Such integrated systems allow combining results from different sensors — satellite images, photogrammetry, LiDAR, GNSS observations,

multi-frequency radar data — into a single model capable not only of classifying objects but also of dynamically adjusting their geometry according to more accurate sources. For example, building contours detected on an orthophoto map using a segmentation network can be automatically refined using laser scanning data with an accuracy of 2–5 cm. This approach has been implemented in Google Research's study, "Buildings Detection from Aerial Imagery Using Deep Learning" (DOI:10.1109/CVPRW53098.2021.00261), where vectorization accuracy is increased by combining CNN segmentation and LiDAR elevation models.

It is also important to emphasize the role of multimodal learning methods, where models simultaneously work with different types of data: spectral channels of satellite images, textures, point clouds, digital terrain models, and sets of geometric primitives. Multimodal architectures, such as FusionNet, MMF-Transformer, and Deep Multimodal Geospatial Fusion Model, allow not only semantic segmentation but also the automatic creation of complex vector layers, including: plot boundaries, buildings, roads, utility networks, hydrographic objects, and relief boundaries. Combined with intelligent self-attention mechanisms, models can improve results by identifying context — for example, understanding that a building cannot cross a riverbed or that a road object has topological continuity.

One practical scenario is the automated interpretation of topographic plans. Digitized plans at scales of 1:500, 1:1000, and 1:2000 are often presented as raster images containing elevation marks, contour lines, utility networks, inscriptions, hatching, and survey control points. The use of deep neural networks allows these objects to be distributed by semantic classes, automatically recognized, and converted into vector layers. This is especially important for creating topographic plans in CAD and GIS (AutoCAD, Digitals, QGIS), as well as for further integration with urban planning documentation.

A particularly promising area is the automated recognition and vectorization of contour lines, which is one of the most labor-intensive stages in the creation of digital terrain models. Traditional methods require significant operator involvement, as contour lines vary in brightness, have interruptions, superimposed labels, and changing elevation

values. In contrast, modern models such as ContourNet, TopoResNet, and AI-Contour Mapping System are capable of automatically selecting contour lines, recognizing their heights using OCR methods, and constructing a digital terrain model (DTM) without the intervention of a specialist. This allows old topographic plans to be converted into modern digital models suitable for terrain analysis, water flow modeling, flood assessment, design modeling, and engineering calculations.

Another area is the automated recognition of engineering infrastructure networks using orthophoto, thermal imaging, multispectral, or radar data. For example, heating networks can be automatically detected using thermal camera data (including drones), and machine learning models can reproduce pipeline routes based on temperature anomalies. Water supply and sewerage networks can be detected by the nature of linear changes in the terrain or destructive features on the surface. The LineFormer, TranSeg, and Att-UNet algorithms allow these objects to be accurately reproduced even in old areas of the city where the networks are incomplete or contain errors.

Geospatial data consistency methods are also important, where classification and vectorization not only create layers but also ensure topological correctness without violating GIS rules: closed polygons, no self-intersections, correct linear networks, and no duplicates. Intelligent systems are capable of automatically finding errors in vector data and correcting them, minimizing the number of artifacts. This is of great importance for cadastral work, since automatic topological validation allows avoiding overlaps of land plots, gaps between boundaries, and errors in the structure of polygons.

Modern technologies open up the possibility of creating intelligent systems for updating cartographic information in near-real-time. Multispectral satellite systems (Sentinel-1, Sentinel-2, WorldView-3, PlanetScope) and drones provide regular image updates, while AI algorithms automatically compare new and old data, identify changes, perform intelligent vectorization of new objects, and update GIS. This is extremely relevant for Ukrainian municipalities, which are required to monitor construction, illegal logging, quarry expansion, and changes in agricultural land use.

The final stage of modern classification and vectorization systems is the application of generative models for reconstructing missing data. For example, if part of

a topographic map is damaged or worn out, GAN models can reconstruct the missing areas with high accuracy. In the case of point clouds, NeRF and Gaussian Splatting models allow three-dimensional objects to be restored as highly accurate polygonal models. This is important when working with areas that have suffered military destruction or natural disasters.

Intelligent vectorization increasingly includes spatial prediction modules, where artificial intelligence not only identifies existing objects but also predicts possible directions of development: for example, models can automatically complete fragmentary roads, estimate the potential boundaries of objects based on available data, and suggest the most likely routing options. Such approaches are used in map update systems in navigation services and in digital city twins.

An important component of modern intelligent geodata classification and vectorization systems is their ability to adapt to different sources, shooting modes, and terrain types. In traditional approaches, models had to be retrained for each new territory, season, or sensor, which was very time-consuming and resource-intensive. In contrast, modern architectures that use the transfer learning and domain adaptation paradigms allow the model to be adapted to a new territory without complete retraining. For example, a system trained on Sentinel-2 data for urban classification can be adapted to the finer resolution of PlanetScope or to Sentinel-1 radar images with just a few hundred local examples. This provides high flexibility and significantly reduces the cost of creating and updating maps.

Few-shot learning and zero-shot segmentation technologies also play an important role, allowing systems to work with a limited amount of labeled data or even without it. In geodesy, this is particularly relevant for areas where there are no high-precision cadastral or cartographic materials, and the terrain is changing rapidly — as in the case of areas affected by armed aggression or natural disasters. For example, the Segment Anything (SAM) model is capable of vectorizing buildings and roads without special training, using only contextual image features, which makes it extremely valuable for urgent mapping.

A particularly important area is the intelligent combination of results from

different models (model ensemble). In these systems, several segmentation or classification models work in parallel, and their results are reconciled through ensemble mechanisms — average voting, weighted combination, confidential indices, Bayesian aggregation. This not only improves accuracy but also ensures stability when working in complex areas where one method may be effective for vegetation, another for buildings, and a third for networks. Ensemble approaches are successfully used in ESA topographic services and within the EU Copernicus program to populate the High Resolution Layers (HRL) database, where the accuracy of semantic segmentation is increased by 10–20%.

Deep learning has also radically transformed the process of automatic determination of land cover and land use types. Models such as DeepLabv3+, Swin-Transformer-Large, and MAE GeoVision allow territories to be divided into dozens of classes: agricultural land, forest areas, wetlands, industrial development, transport corridors, technical sites, open soils, etc. Unlike classical spectral classification methods, intelligent systems take into account textural, contextual, structural features, and spatial relationships between objects. This makes the result more accurate and resistant to seasonal changes and atmospheric influences.

In surveying practice, intelligent post-classification editing methods (post-processing AI) are increasingly being used to clean up vectorized objects from errors. Such systems are capable of:

- eliminating "holes" in building contours;

- smooth out irregularities;

- automatically close polygons;

- correct geometric distortions;

- remove redundant nodes in linear objects;

- correct topological conflicts;

- reconcile attribute information.

It is worth noting that the Topology-GNN and DeepTopoFix algorithms demonstrate the ability to automatically correct vector data in urban planning and cadastral tasks, reducing the number of topological errors by more than 80%.

Another promising area is the development of intelligent contextual systems that take into account not only the object itself, but also its position in space, functional purpose, and neighboring objects. For example, the GeoContext Vision Transformer and ST-GNN models are able to "understand" that industrial objects are usually located near transport routes, and residential buildings are located in a structured neighborhood grid. This not only improves classification accuracy, but also corrects erroneous vectorizations through logical analysis of the spatial structure.

Vectorization is also closely related to methods for reconstructing missing map fragments, where generative models such as GANs, Diffusion Models, and Variational Autoencoders demonstrate the ability to restore heavily damaged map fragments. When working with archival topographic plans or land inventory materials, this technology makes it possible to restore the complete contours of objects while preserving their geometry and style. The parallel use of GAN reconstruction and segmentation vectorization allows for the complete automation of the digitization process for old geodetic documents.

It is important to emphasize that intelligent automated classification and vectorization systems play a key role in performing dynamic monitoring tasks, particularly in urban planning, land management, environmental analysis, and risk management. For local communities, this means the ability to quickly identify illegal construction, changes in land use, land degradation, coastal strip violations, deforestation, and riverbed erosion. Intelligent systems track changes in near-real-time and generate vector layers ready for integration into the community's GIS portal.

Given the rapid development of technology, intelligent classification and vectorization systems are becoming the foundation of digital twins of territories, enabling the creation of comprehensive models for analyzing, forecasting, and managing urban and rural spaces. By combining deep models, computing platforms, and large geodata arrays, it is possible to automate the entire processing cycle — from collecting primary measurements to creating highly accurate vector models.

4 INTEGRATION OF INTELLIGENT DATA PROCESSING INTO MUNICIPAL GEOINFORMATION SYSTEMS

4.1 Architecture of municipal GIS with intelligent modules

The current stage of development of municipal geographic information systems is characterized by a transition from classic information and reference platforms to complex integrated management decision support systems, in which intelligent methods of spatial data processing play a key role. This transformation is driven by the growth in the volume of geodetic and geospatial information, the increasing complexity of the management tasks of local communities, and the need for rapid analysis of multifactorial spatial processes. In this context, the architecture of municipal GIS with intelligent modules is seen as a systemic basis for the integration of geodata, analytical models, and decision support mechanisms in a unified digital environment. [2].

Architecturally, municipal GIS are traditionally built on a multi-level principle, which involves the separation of data storage, processing, analysis, and visualization functions. In classic systems, the main focus was on the formation of geodatabases and cartographic services, while analytical capabilities were limited to standard spatial analysis tools. The integration of intelligent modules fundamentally changes this architecture, complementing it with a level of intellectual processing that allows for the automation of spatial pattern analysis, the forecasting of territorial development, and the formation of recommendations for management decisions (fig. 4.1). [8].

The basic element of the municipal GIS architecture with intelligent modules remains the data level, which includes geodetic measurements, cadastral information, remote sensing data, sensor observations, and statistical data. It is at this level that the spatial-temporal framework of the system is formed, ensuring the integration of diverse sources of information. The quality and structure of this level directly determine the effectiveness of intelligent modules, since artificial intelligence algorithms are sensitive to errors, inconsistencies, and gaps in data. [25].
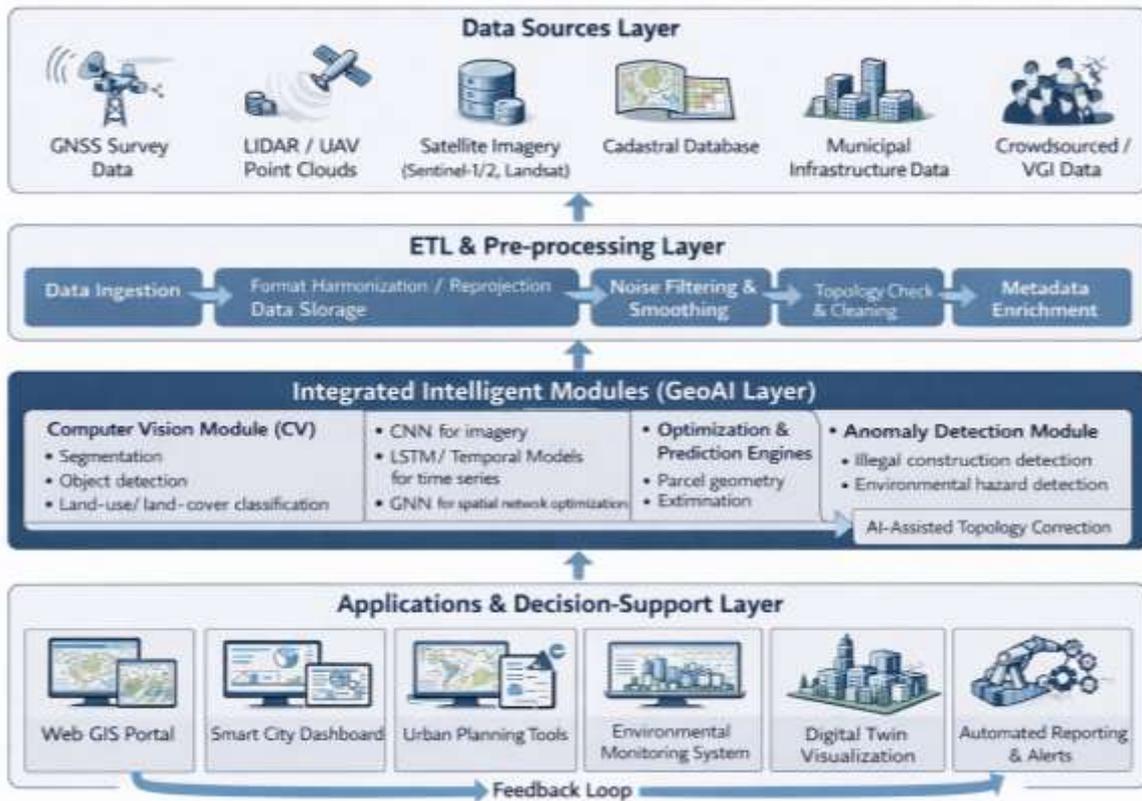
*Fig. 4.1 — Generalized architecture of a municipal geographic information system
with integrated intelligent modules*

Above the data level, there is a level of preliminary processing and integration, within which cleaning, normalization, transformation of coordinate systems, and conversion of geodata to a single spatial environment are performed. In municipal GIS, this level performs the critical function of ensuring the methodological readiness of data for intelligent analysis, as justified in the previous section of the monograph. It is here that quality control mechanisms are implemented, sets of information from different times and scales are harmonized, and structured data sets are formed for further modeling. [76].

The key difference between intellectually oriented municipal GIS architecture is the presence of a separate level of intellectual processing, which includes modules for machine learning, neural network modeling, spatial classification, and forecasting. These modules can be implemented both as built-in components of the GIS platform and as external services integrated through software interfaces. This approach ensures

architectural flexibility, computational scalability, and the ability to adapt the system to the specific needs of a particular territorial community [130].

Above the intellectual level is the level of applied services and decision support, within which the results of analysis are transformed into forms that are understandable to users. Such services include geoinformation dashboards, scenario models, risk indicators, and territory monitoring systems. In municipal GIS, this level acts as an interface between complex intellectual algorithms and managers, ensuring that results are interpretable and can be used in planning and management processes [2].

An important feature of municipal GIS architecture with intelligent modules is its focus on service-oriented and modular organization. This approach allows for the gradual expansion of the system's functionality, the integration of new intelligent models, and the adaptation of the architecture to changes in the regulatory environment and management needs. In the practice of digital transformation of local communities, modular architecture is considered the most promising, as it ensures the long-term viability of geoinformation systems and their ability to develop [9].

Thus, the architecture of municipal GIS with intelligent modules is a multi-level system in which geodetic data, intelligent algorithms, and management services are integrated into a single digital environment. It is this architecture that creates the prerequisites for the transition from reactive territory management to a proactive and predictive approach based on the use of artificial intelligence and neural network modeling. This justifies the need for a detailed consideration of specific mechanisms for integrating intelligent modules into municipal GIS.

4.2   Geoanalytical geodata processing pipeline

The integration of intelligent methods into municipal geoinformation systems is impossible without the formation of a formalized geoanalytical pipeline for processing geodata, which in modern scientific literature has been named the GeoAI pipeline. Such a pipeline is a sequentially organized chain of procedures for collecting, preparing, analyzing, modeling, and interpreting geospatial information using artificial

intelligence methods. In the context of municipal GIS, the GeoAI pipeline acts as a system-forming mechanism that ensures coordinated interaction between geodetic data, intelligent models, and management services of territorial communities [4].

Conceptually, the GeoAI pipeline is based on the idea of a continuous cycle of transforming data into knowledge, where each stage has a clearly defined functional role and methodological load. Unlike traditional GIS workflows, where analysis is often fragmented, the geospatial analytics pipeline ensures the integrity and reproducibility of results. This is particularly important in municipal systems, as management decisions must be based on transparent and scientifically sound spatial data analysis procedures (fig. 4.2) [132].
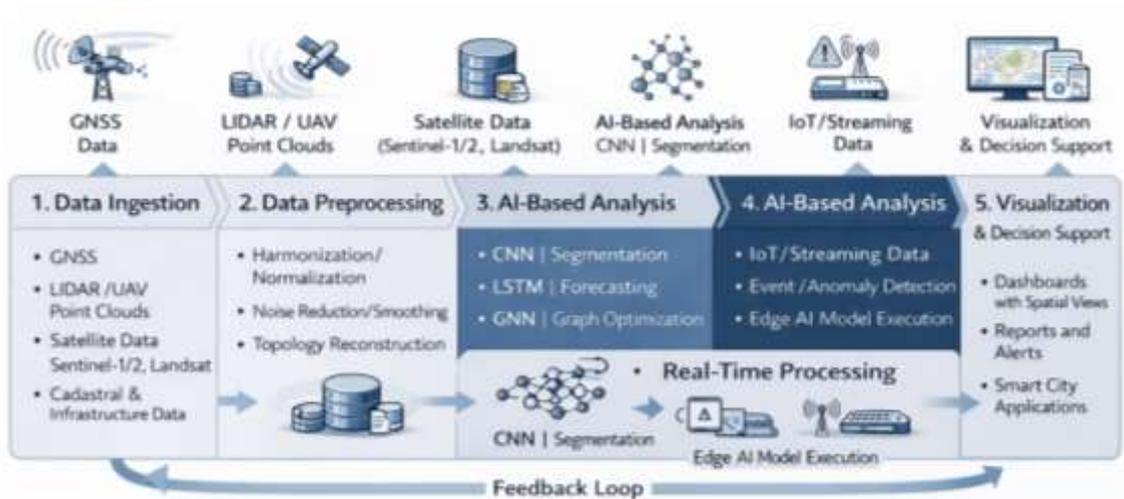
Fig. 4.2 — GeoAI pipeline for processing geodata in municipal geographic information systems

The initial stage of the geoanalytical pipeline is the formation of an input array of geodata, which includes the results of geodetic measurements, cadastral information, remote sensing data, sensor network data, and statistical information. In municipal GIS, this stage is associated with ensuring the completeness, relevance, and spatial consistency of data, which is a necessary prerequisite for further intelligent analysis. At this stage, the input geodata is not yet suitable for direct application of machine learning methods and requires comprehensive pre-processing, which was discussed in detail in Chapter 2.

The next stage of the GeoAI pipeline involves preparing and transforming geodata into a format suitable for intelligent modeling. It is at this level that the procedures of cleaning, normalizing, scaling, and forming a feature space are implemented, which ensure the methodological readiness of data for use in artificial intelligence algorithms. In municipal GIS, this stage is particularly important due to the spatial heterogeneity of data and the need to take into account the territorial context, which directly affects the quality of the models built [80].

The central element of the geoanalytical pipeline is the level of intelligent analysis and modeling, which applies algorithms of machine learning, neural network analysis, spatial classification, and forecasting. In municipal GIS, such algorithms are used to solve a wide range of tasks, including assessing the condition of territories, identifying anomalies in land use, forecasting infrastructure loads, and modeling scenarios for the development of territorial communities. An important feature of this stage is its close connection with the spatial context, which distinguishes the GeoAI pipeline from classic analytical pipelines in the field of data science [2].

After performing intellectual analysis, the modeling results move on to the stage of interpretation and integration into municipal GIS application services. At this stage, the results of machine learning are transformed into spatially understandable forms — risk maps, development indicators, and scenario models. For local governments, this level is the most significant, as it ensures the practical use of GeoAI pipeline results in the processes of planning, monitoring, and managing territorial communities [9].

The final component of the geospatial analytics pipeline is feedback and model update mechanisms that ensure the system adapts to changes in the spatial environment. In municipal GIS, this means constantly updating geodata, retraining intelligent models, and adjusting management decisions based on new information. This approach transforms the GeoAI pipeline into a dynamic system capable of responding to changes in territorial development in near real time.

Thus, the GeoAI pipeline is a key element in the integration of intelligent data processing into municipal geographic information systems. It ensures the integrity, reproducibility, and scientific validity of geodata analysis processes, creating a

methodological basis for building intelligent management decision support systems. This is precisely what necessitates further consideration of the implementation of the GeoAI pipeline in the form of applied services and management tools.

4.3   Integration of artificial intelligence models with spatial databases

The integration of artificial intelligence models with spatial databases is a key prerequisite for the practical implementation of intelligent functions in municipal geographic information systems. Spatial DBMSs are used to concentrate, coordinate, and store geodetic and geospatial data for long periods of time, forming the basis for analytical and predictive tasks in territorial management. The use of platforms such as PostGIS or other Spatial DBs allows combining the advantages of a relational data model with the capabilities of spatial analysis and creating an effective environment for integrating intelligent models into the production processes of municipal GIS [131].

In classical GIS architecture, spatial databases mainly served as repositories for geometry and attribute information, providing access to data for mapping and standard spatial analysis. The integration of artificial intelligence models fundamentally expands the functional purpose of Spatial DBs, transforming them into an active component of the GeoAI pipeline. In this case, the spatial database not only stores the source geodata, but also provides training samples, supports the storage of modeling results, and serves as an environment for spatial interpretation of forecasts and scenario assessments (fig. 4.3). [132].

PostGIS, as an extension of the PostgreSQL DBMS, is one of the most widely used tools for implementing spatial databases in municipal GIS. Its functionality includes storing different types of geometries, supporting coordinate systems, spatial indexes, and a wide range of spatial analysis functions. For the integration of artificial intelligence models, it is important that PostGIS allows for pre-aggregation, filtering, and spatial queries directly at the database level, reducing the amount of data transferred and increasing the efficiency of intellectual processing [133].
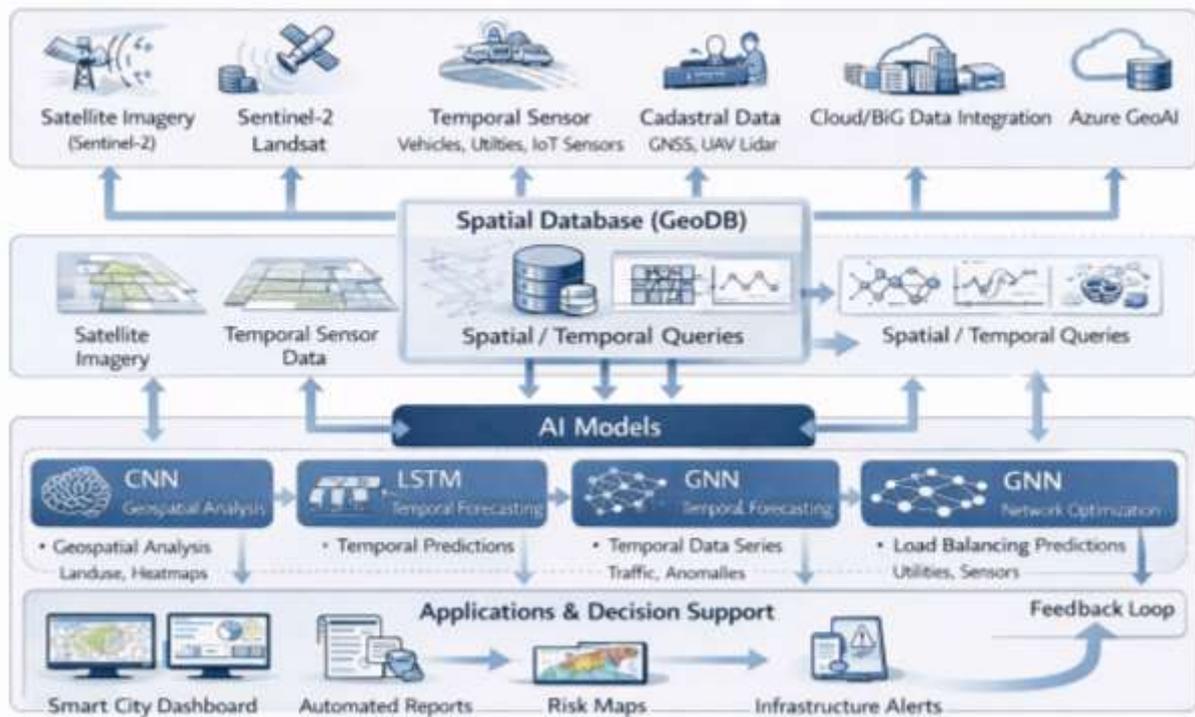
*Fig. 4.3 — Scheme for integrating artificial intelligence models with spatial
databases in municipal geographic information systems*

The integration of AI models with spatial databases in municipal GIS is usually implemented through a clearly defined data exchange between Spatial DB and the analytical environment in which machine learning algorithms are executed. In this process, the spatial database acts as a source of structured training data formed on the basis of spatial and attribute features. After training the model, the prediction or classification results are returned to the Spatial DB in the form of new attributes, thematic layers, or aggregated indicators that can be directly used in geoinformation services [4].

A distinctive feature of AI integration with spatial databases is the need to take into account spatial autocorrelation and topological relationships between objects. Unlike classical tabular data, spatial objects are not independent observations, which significantly affects the model training process. Spatial databases allow samples to be formed taking into account the proximity, distances, and hierarchy of objects, which increases the accuracy and generalizability of intelligent models in territorial nalysis tasks [81].

In municipal GIS, the integration of AI models with Spatial DB has important practical significance for supporting management decisions. Storing the results of intelligent analysis directly in a spatial database ensures their spatial interpretability, repeatability, and long-term usability. This allows local authorities to perform comparative analysis of territorial development scenarios, assess the dynamics of change, and use the results of modeling as an element of official information and analytical systems [2].

An important aspect of integrating intelligent models with spatial databases is the issue of scalability and performance. Municipal GIS operate with large volumes of geodata, which requires query optimization, the use of spatial indexes, and efficient organization of modeling results storage. Spatial DBMSs, such as PostGIS, provide the necessary optimization mechanisms, allowing AI models to be integrated into the production contours of municipal information systems without loss of performance [131].

Thus, the integration of artificial intelligence models with spatial databases is a key element of the architecture of intelligence-oriented municipal GIS. It provides a link between geodetic data, intelligent algorithms, and application services, creating the basis for the implementation of full-fledged decision support systems at the local community level. This is precisely what necessitates further consideration of application scenarios for the use of GeoAI in municipal management, which is the subject of the next sub-section.

4.4 ETL processes and automated processing of geospatial data streams

Modern municipal geoinformation systems operate in conditions of constantly growing volumes of geodetic and geospatial information coming from diverse sources in near real time. Geodetic measurements, satellite and aerial photography results, data from sensor networks, IoT devices, transport systems, and urban services form continuous streams of geodata that require rapid processing, integration, and analytical processing. In these conditions, traditional approaches to periodic database updates are

becoming insufficient, necessitating the implementation of automated ETL processes as a basic mechanism for integrating streaming geodata into municipal GIS [2].

ETL (Extract – Transform – Load) processes in the context of geographic information systems should be viewed not only as a technical procedure for transferring data between systems, but also as a methodologically significant element of the architecture of intelligent municipal GIS. It is through ETL conveyors that "raw" geodata is transformed into a structured, coordinated, and methodologically ready information resource suitable for further spatial analysis and the application of artificial intelligence methods. In the case of streaming data, ETL processes become more complex, as they must ensure not only the correctness but also the efficiency of processing continuous information flows (Fig. 4.4) [4].
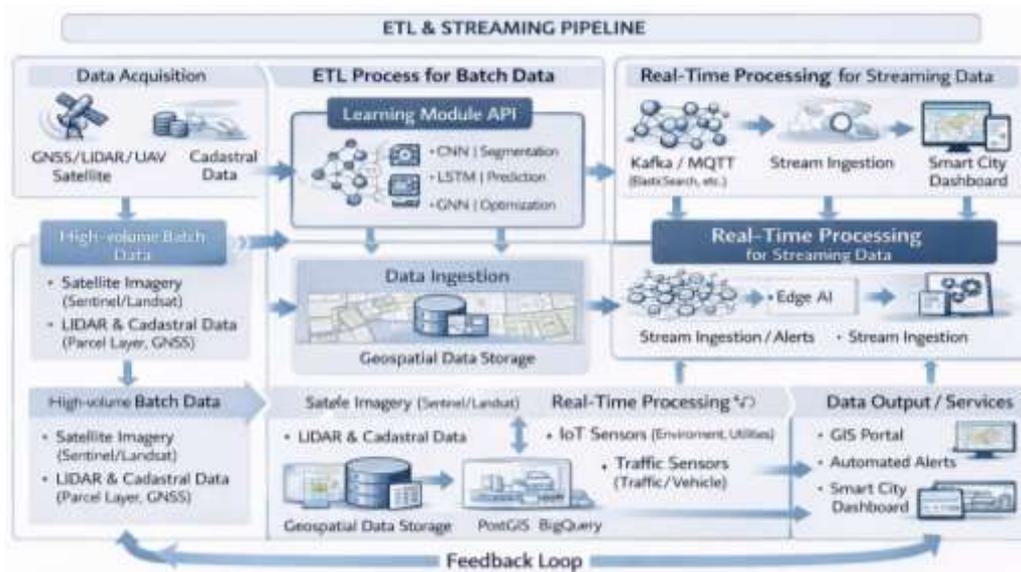
Fig. 4.4 — ETL pipeline and automated processing of streaming geodata in municipal geographic information systems

The data extraction stage in geoinformation ETL processes is characterized by an extraordinary variety of sources. In municipal GIS, these can include surveying instruments, GNSS receivers, laser scanners, satellite remote sensing platforms, urban sensor networks, video surveillance systems, and open geoportals. Each of these sources generates data in its own formats, coordinate systems, and time scales, which

poses serious challenges for automated information extraction. ETL mechanisms must ensure not only stable access to sources, but also control over the completeness, integrity, and relevance of streaming geodata [9].

The most methodologically complex component of ETL processes in municipal GIS is the data transformation stage. This is where procedures for bringing geodata into a single spatial environment, normalizing attribute characteristics, eliminating errors, and preparing information for intelligent analysis are implemented. For streaming geodata, the transformation must be performed automatically and with minimal delays, which requires the use of optimized algorithms and streaming computing architectures. In this context, ETL processes effectively become part of the GeoAI pipeline, ensuring the methodological readiness of data for machine learning. [80].

Working with spatio-temporal characteristics is particularly important in the transformation of streaming geodata. Unlike static sets, streaming data constantly changes over time, which requires correct synchronization of timestamps, aggregation of data at specified time intervals, and preservation of change history. In municipal GIS, this is critical for infrastructure monitoring, traffic flow analysis, environmental monitoring, and emergency management. In this case, ETL processes act as a filter and structurer of information, transforming continuous data streams into analytically usable spatiotemporal structures. [81].

The data loading stage within ETL processes is closely related to the spatial databases discussed in the previous subsection. For streaming geodata, loading should be performed incrementally, taking into account the high frequency of updates and system performance requirements. Spatial DBMSs, such as PostGIS, provide the necessary mechanisms for the efficient storage and indexing of large volumes of dynamic geodata, allowing the integration of ETL processing results without disrupting the stability of municipal GIS [131].

Automation of ETL processes in municipal GIS is a prerequisite for scaling intelligent territory management systems. Manual or semi-automatic processing of geodata cannot provide the necessary speed of response to changes in the urban

environment. Automated ETL pipelines minimize the human factor, increase process reproducibility, and ensure stable quality of data fed into the system's intelligent modules [2].

In the context of GeoAI, the interaction between ETL processes and machine learning models deserves special attention. Streaming geodata can be used not only to generate input data, but also to continuously update and retrain models. Thus, ETL processes become part of a closed loop of adaptive management, in which data, models, and management decisions are in constant interaction. This allows municipal GIS to move from static analytical scenarios to dynamic forecasting and response systems. From a methodological point of view, ETL processes and automated processing of geospatial data streams are a key factor in the integration of artificial intelligence into municipal management practices. They provide a continuous link between real spatial processes and digital models of territorial development. Combined with intelligent data analysis algorithms, ETL pipelines form the basis for creating adaptive, predictive, and resilient next-generation geoinformation systems. Thus, ETL processes in municipal geoinformation systems go beyond being a supporting tool and become a fundamental component of GeoAI architecture. They ensure the integration of streaming geodata, support intelligent models, and create conditions for the implementation of full-fledged management decision support systems. This logically leads to the need for further analysis of applied scenarios for the use of intelligent geodata processing in municipal management.

4.5   Intelligent decision support services in local communities

Modern local communities operate in an environment of increasing complexity of socio-economic, spatial, and infrastructural processes, which requires a shift from intuitive or reactive approaches to management to systematic, scientifically based decision-making. In this context, intelligent decision support services implemented on the basis of municipal geoinformation systems are considered a key tool for the digital transformation of territorial management. Such services combine geodetic and

geospatial data, the results of intelligent analysis, and visualization mechanisms in a single information and analytical environment focused on the needs of local governments. [2].

Intelligent decision support services in local communities are based on the integration of GeoAI process results with applied management tasks. Unlike traditional GIS systems, which mainly perform data storage and visualization functions, intelligent services provide analytical interpretation of spatial information, automated assessment of development scenarios, and recommendations for management actions. Thus, the geographic information system ceases to be a passive tool and becomes an active element of the management circuit of the territorial community (fig. 4.5) [4].

Fig. 4.5 — Intelligent services to support management decision-making in local communities based on municipal GIS

Functionally intelligent decision support services cover a wide range of management tasks related to spatial planning, infrastructure management, environmental monitoring, and risk assessment. They allow for the aggregation of large volumes of geodata, the performance of multifactorial analysis, and the presentation of results in the form of understandable indicators, spatial models, and scenario forecasts. For local community leaders, this creates an opportunity to quickly assess the current state of the territory, compare alternative development options, and make decisions that take into account the spatial specifics of the community [8].

An important feature of intelligent services is their focus on scenario modeling. Based on the results of machine learning and neural network analysis, such services allow forecasting the development of territories under various conditions of managerial influence. This is particularly relevant for local communities in the context of decentralization, when local authorities are given expanded powers in the areas of land use, infrastructure development, and natural resource management. In this case, intelligent decision support services serve as a tool for assessing the consequences of management actions before they are actually implemented [2].

From a methodological point of view, intelligent decision support services must ensure transparency and interpretability of results. Artificial intelligence algorithms used in municipal GIS often have a complex internal structure that is not sufficiently understandable to end users. Therefore, an important task is to transform the results of modeling into forms that can be interpreted by managers without special training in data science. Geoinformation dashboards, interactive maps, and analytical reports play a key role in ensuring such a connection between intelligent models and the decision-making process [80]

In the practice of local communities, intelligent decision support services contribute to improving the soundness and consistency of management actions. The use of spatially oriented indicators allows identifying problem areas of development, assessing the efficiency of resource use, and responding to negative trends in a timely manner. It is particularly important that such services provide a single information field for various structural units of local self-government bodies, reducing the level of fragmentation of management decisions and increasing their strategic coordination [9].

Intelligent decision support services also play an important role in communication between local authorities and the public. Visualizing the results of spatial analysis in the form of open geoportals and interactive maps helps increase management transparency, engage citizens in planning processes, and build trust in management decisions. In this regard, municipal GIS with built-in intelligent services become a tool not only for management but also for public dialogue on territorial development.

Thus, intelligent decision support services in territorial communities are the final element of the integration of artificial intelligence into municipal geographic information systems. They ensure the transition from data analysis to practical management actions, combining a geodetic basis, intelligent models, and management mechanisms into a single system. It is these services that determine the real value of GeoAI for territorial communities and create the foundation for the further development of intelligence-oriented municipal management.

5 APPLICABLE SCENARIOS AND PROSPECTS FOR THE DEVELOPMENT OF INTELLIGENT GEODATA PROCESSING

5.1 Use of intelligent geodata processing in municipal management

Modern municipal management increasingly operates in conditions of high spatial complexity, dynamic processes and multifactorial uncertainty, which significantly complicates effective management decision-making at the level of local communities. Land use, the development of engineering and transport infrastructure, the ecological state of territories, residential development, social processes and security challenges have a distinct spatial nature and are interconnected through complex nonlinear dependencies. In such conditions, traditional management approaches based on fragmentary statistical data or expert assessments prove to be insufficient. This is precisely what determines the growing role of geoinformation systems in municipal management and creates the preconditions for the integration of artificial intelligence and neural network modelling methods into the processes of analysis and decision support. [2].

Intelligent processing of geodata in municipal management is seen as an evolutionary stage in the development of geographic information systems, enabling the transition from descriptive and reactive management to predictive, scenario-based and adaptive management. Unlike classic GIS, which mainly perform storage, visualisation and standard spatial analysis functions, intelligence-oriented municipal GIS are capable of automatically identifying spatial patterns, predicting the consequences of management decisions and forming recommendations based on a comprehensive analysis of large volumes of geodata. In this context, geodata ceases to be a passive information resource and acquires the status of an active tool for managing the development of territorial communities (fig. 5.1) [4].

*Fig. 5.1 — The role of intellectual processing of geodata in the system of municipal
management of territorial communities*

A distinctive feature of municipal management is that most management decisions have a clear spatial reference. Decisions on the location of infrastructure facilities, changes in the functional use of land, reconstruction of transport networks or development of residential areas directly affect the spatial structure of the community's territory. Intelligent processing of geodata allows these spatial aspects to be taken into account in a comprehensive manner, combining the geometric, attributive, temporal and contextual characteristics of the territory in a single analytical space. This enables local authorities to move from local decisions to strategic management of territorial development [8].

The use of intelligent geodata processing in municipal management is closely linked to the concept of evidence-based management, whereby management decisions are made on the basis of objective data analysis rather than solely on expert judgement. Geographic information systems with integrated artificial intelligence algorithms allow for the formation of quantitative indicators of the state of territories, assessment of the efficiency of resource use, and forecasting of spatial processes. This approach

contributes to more informed decisions, reduced risks, and more transparent management of local communities. [80].

One of the key areas of application of intelligent geodata processing in municipal management is land resource management. Land plots, development zones, nature conservation areas and other elements of land use form a complex spatial system in which decisions regarding some objects inevitably affect others. Intelligent models allow analysing the structure of land use, identifying conflicts between different types of land use, and predicting the consequences of changes in urban planning documentation. Combined with high-precision geodetic data, this creates a powerful tool for the rational management of the land fund of territorial communities [81].

Another important area of application for intelligent geodata processing is the management of engineering and transport infrastructure. Municipal GIS systems allow data on water supply, heat supply, electricity supply, transport flows and public infrastructure facilities to be integrated into a single spatial model. The application of machine learning methods based on this data makes it possible to identify potential problem areas, predict network loads and optimise infrastructure development plans. As a result, management decisions are based not only on the current state of the systems, but also on forecasts of their future functioning [2].

Intelligent processing of geodata also plays an important role in emergency monitoring and response systems. Spatial data on terrain, hydrological conditions, buildings and infrastructure enable the creation of models of risks of flooding, landslides, man-made accidents and other hazardous processes. Integrating these models into municipal GIS systems enables rapid analysis of situations and supports decision-making in crisis conditions. In this context, artificial intelligence acts as a tool for increasing the adaptability and resilience of local communities to external and internal challenges [9].

From an organisational point of view, the introduction of intelligent geodata processing in municipal management changes the very logic of local government work. Management decisions are increasingly based on interdisciplinary interaction between specialists in the fields of geodesy, GIS, information technology and public

administration. Municipal GIS with built-in intelligent modules are becoming a common platform for data exchange, analysis and coordination of actions between different structural units of the community. This contributes to the formation of a unified information space for territorial development management.

Thus, the use of intelligent geodata processing in municipal management forms a qualitatively new approach to the management of territorial communities. The combination of geodetic accuracy, geoinformation integration and intelligent analysis creates the conditions for a transition from fragmented management decisions to systematic, predictive and adaptive management of territorial development.

The further development of intelligent geodata processing in municipal management is associated with the transition from general analytical functions to solving specific management tasks that directly affect the socio-economic development of territorial communities. At this stage, GeoAI ceases to be merely a tool for analysing spatial data and acquires the features of a full-fledged element of the management mechanism, integrated into the processes of planning, monitoring and evaluating the effectiveness of management decisions. Such integration provides the opportunity to move from intuitive management to a formalised, data-driven approach, which is particularly relevant in the context of decentralisation and the growing responsibility of local authorities for territorial development [2].

One of the key areas of application for intelligent geodata processing is spatial analysis support for strategic and operational planning. Municipal development plans, socio-economic growth programmes, master plans for settlements and detailed plans for territories have a clearly defined spatial dimension. Intelligent geoinformation systems make it possible to analyse the compliance of such documents with the actual state of the territory, identify potential conflicts between different types of land use, and predict the consequences of implementing planning decisions. Thanks to the use of machine learning algorithms, these processes can be automated, which significantly increases the efficiency of planning activities by local authorities (fig. 5.2) [8].
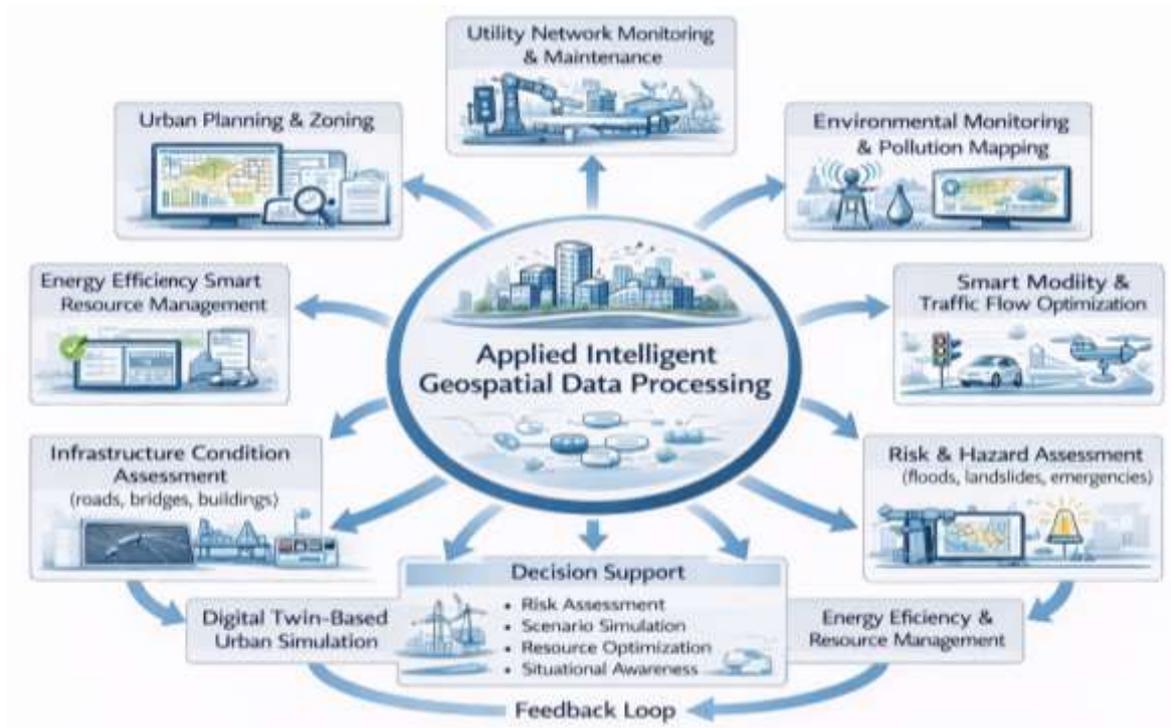
Fig. 5.2 — Applied areas of use of intelligent geodata processing in municipal management

An important aspect of municipal management is the optimisation of the use of local community resources, in particular land, infrastructure and natural resources. Intelligent geodata processing allows the creation of comprehensive spatial models of a territory's resource potential, which take into account not only the availability of resources, but also their accessibility, condition and potential for further use. Such models provide a basis for making informed decisions on investment, infrastructure development and the conservation of natural areas. In this context, GeoAI acts as a tool for ensuring the sustainable development of territorial communities, combining economic, environmental and social aspects of management.[81].

The role of intellectual processing of geodata in risk and security management systems of territorial communities requires separate consideration. Natural and man-made threats, in particular flooding, landslides, engineering network accidents, fires and transport incidents, have a clear spatial location and depend on many factors. The integration of geodetic data, remote sensing materials and statistical indicators within municipal GIS allows for the construction of intelligent risk models that take into

account both spatial and temporal patterns. This enables local authorities to move from reactive responses to emergencies to preventive risk management [9].

In municipal management practice, intelligent processing of geodata is also used to evaluate the effectiveness of implemented management decisions. After the implementation of infrastructure projects, changes in land use or environmental programmes, municipal GIS can be used to analyse actual changes in the spatial structure of the territory. Comparing forecast scenarios with actual data allows for the identification of deviations, assessment of the achievement of set goals, and adjustment of further management actions. Thus, GeoAI provides feedback in the territorial development management system, which is a necessary condition for its adaptability and sustainability.

An important area of application for intelligent geodata processing is the support of budget planning and financial management processes at the local government level. Spatial analysis allows financial expenditures to be linked to specific territories, infrastructure objects or social groups of the population. Intelligent models based on geodata can be used to assess the effectiveness of budget investments, forecast economic effects and optimise resource allocation. This contributes to greater transparency in the budget process and ensures more rational use of community financial resources [2].

Intelligent processing of geodata also plays an important role in public participation and communication systems between local authorities and the population. Geoinformation services based on the results of spatial analysis and modelling allow for the visualisation of management decisions, the demonstration of alternative development scenarios, and the involvement of citizens in the discussion of strategic issues. This is particularly relevant in the context of decentralisation, when the importance of openness and accountability of local authorities is increasing. In this context, intelligent GIS become a tool for building trust and partnership between the community and government bodies.

The organisational implementation of intelligent geodata processing requires a change in approaches to the management of information resources of territorial

communities. It is necessary to create interdisciplinary teams capable of combining competencies in the fields of geodesy, geoinformation technologies, data analytics and public administration. Municipal GIS are becoming a central element of the community's information infrastructure, coordinating the actions of various departments and forming a unified vision for the development of the territory.

Thus, intelligent processing of geodata in municipal management provides comprehensive support for planning, resource management, risk assessment, and analysis of the effectiveness of management decisions. It creates conditions for the transition to adaptive, evidence-based management capable of responding to dynamic changes in the spatial environment.

The final dimension of the use of intelligent geodata processing in municipal management is related to the profound institutional changes taking place in the system of territorial community management under the influence of digital transformation. The integration of artificial intelligence, neural network analysis and geoinformation technologies is not limited to the implementation of individual software tools, but leads to a rethinking of the role of data, decision-making procedures and the functions of local government bodies. In this context, GeoAI is not only a technological but also an institutional factor in the modernisation of municipal management [2].

One of the key consequences of introducing intelligent geodata processing is an increase in the digital maturity of local communities. In this case, digital maturity is determined not only by the availability of modern information systems, but also by the ability of local authorities to systematically use data for analysis, forecasting and strategic planning. Municipal GIS with intelligent modules form a unified information environment within which management decisions are made based on a comprehensive analysis of spatial, socio-economic and environmental factors. This reduces subjectivity in the management process and increases the soundness of strategic decisions (fig. 5.3) [8].
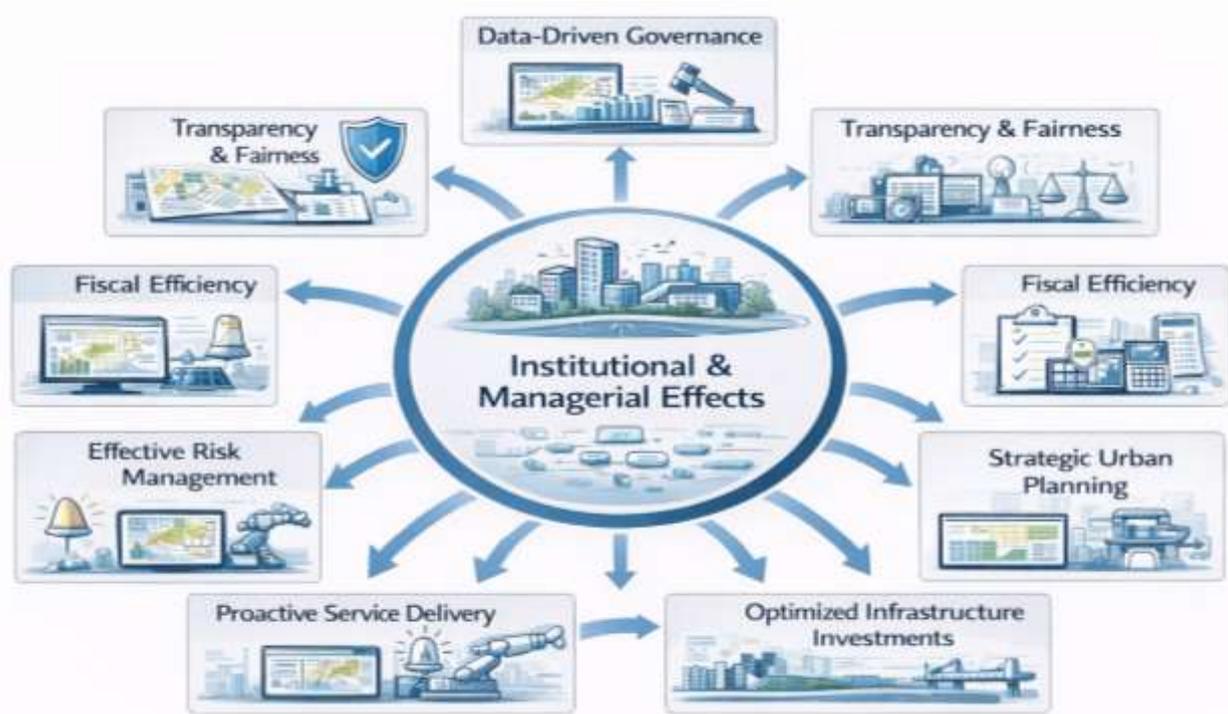
*Fig. 5.3 — Institutional and managerial effects of using intelligent geodata
processing in local communities*

The institutional effect of GeoAI implementation is also evident in changes to
the organisational structure of local community management. The use of intelligent
geoinformation systems requires interdepartmental coordination, as spatial data and the
results of their analysis are used by various structural units — from land and urban
planning services to departments of economy, ecology and civil protection. In this case,
municipal GIS become an integration platform that ensures the coordination of
management actions and promotes the formation of a comprehensive approach to
territorial development. This reduces the fragmentation of management and increases
the effectiveness of the implementation of strategic community development
programmes.

An important aspect of the use of intelligent geodata processing is the
transformation of strategic planning processes. Traditional strategies for the
development of territorial communities were often based on retrospective analysis and
expert assessments, which limited their ability to respond adequately to dynamic
changes in the spatial environment. The use of GeoAI allows for a transition to scenario

and predictive planning, within which possible options for the development of the territory are analysed, taking into account various management decisions. This creates the conditions for the formation of adaptive strategies that can be adjusted during implementation based on new data and the results of intelligent analysis. [4].

The social dimension of implementing intelligent geodata processing in municipal management is linked to increasing the transparency and accountability of local government bodies. Geoinformation services based on the results of spatial analysis and modelling allow for the visualisation of management decisions, demonstrating their spatial consequences and explaining the logic behind decision-making to citizens. This contributes to building trust between the authorities and the population, as well as increasing public participation in the processes of planning and development of territories. In this respect, GeoAI becomes a tool not only for management, but also for communication between different actors in territorial development [9].

The long-term effect of using intelligent geodata processing is manifested in the increased resilience of territorial communities to external and internal challenges. Spatially oriented intelligent models allow for the timely identification of negative trends, assessment of territorial vulnerability, and development of preventive management measures. This is particularly important in the context of climate change, urbanisation pressure and socio-economic instability. Municipal GIS with intelligent modules are becoming the basis for the formation of risk management systems focused on the long-term sustainability and security of communities.

From the perspective of public administration, the implementation of GeoAI requires the development of human resources and the formation of new competencies among local government employees. Data-driven management requires the ability to interpret the results of intelligent analysis, assess their limitations, and use them in the decision-making process. This necessitates the integration of geoinformation technologies, spatial analysis and artificial intelligence into training and professional development programmes for municipal employees. In this sense, the use of intelligent geodata processing has not only a technological but also an educational dimension.

In conclusion, it should be noted that the use of intelligent geodata processing in municipal management is forming a new paradigm of territorial community management based on data, spatial analysis and forecasting. The combination of geodetic accuracy, geoinformation integration and artificial intelligence ensures the transition from fragmented and reactive management practices to systematic, adaptive and strategically oriented management of territorial development.

5.2 Geodetic and GIS solutions for monitoring infrastructure and territories

Monitoring infrastructure and territories in the municipal management system is a complex, multi-level process that combines geodetic measurements, geoinformation analysis and managerial interpretation of results. Territorial communities operate in an environment of constant spatial change associated with the development of buildings, the transformation of engineering networks, the degradation or restoration of natural areas, and the impact of natural and man-made factors. In such conditions, effective management is impossible without the systematic collection of reliable spatial coordinate information and its integration into municipal geoinformation systems [8].

Given the complexity of spatial processes and the increasing intensity of technogenic and anthropogenic loads on urban and rural areas, the geodetic monitoring system in local communities is constantly transforming from traditional approaches to multi-component digital observation complexes. In line with modern requirements, the monitoring of infrastructure facilities is increasingly focused on the integration of high-precision geodetic information with remote observation data flows, sensor networks and geo-analytical models, which makes it possible to assess the condition of engineering structures, transport networks and territories in near real time. This approach significantly reduces uncertainty about the current parameters of infrastructure functioning and creates opportunities for early detection of risk factors, such as deformations, subsidence or structural changes that could lead to disruption of normal operation or emergencies.

The development of technological means has provided opportunities for long-term continuous monitoring based on the concept of permanently operating geodetic points and autonomous sensor nodes. Within such systems, high-precision GNSS receivers, inclinometric sensors, strain gauge modules and laser rangefinders form a single control network that responds to the slightest changes in the geometric parameters of structures and the earth's surface. The data obtained from these devices is automatically sent to the municipal GIS, where it undergoes preliminary processing, normalisation, and integration into a common spatial information database. This allows for the assessment of trends, the determination of the nature of changes in space and time, and the construction of predictive models using modern machine learning methods [134].

Monitoring of transport infrastructure, which in many local communities consists of highly worn-out facilities, is becoming particularly relevant. Geodetic methods focused on analysing the spatial and geometric characteristics of roadways and engineering structures allow for the detection of unevenness, deformation, subsidence, and load-bearing capacity violations that negatively affect traffic safety and road surface durability. In modern practice, photogrammetric surveys of motorways and streets performed using unmanned aerial vehicles have become widespread. Highly detailed orthophoto plans and digital surface models provide a comprehensive reproduction of the actual state of the road network and allow for the rapid inventory of defects, assessment of residual resources, and identification of optimal areas for repair.

In the engineering network condition monitoring system, the combination of geodetic and geoinformation tools with remote monitoring technologies is of particular importance. Underground utilities — water, sewerage, gas and heating networks — are traditionally considered to be highly complex and critical facilities. In many communities, these networks are significantly worn out, which necessitates the implementation of automated solutions for monitoring their technical condition. By integrating pressure, temperature, flow rate, vibration and acoustic characteristics with geoinformation models, it becomes possible to identify potential violations before they

manifest themselves on the surface. This provides a basis for developing accident prediction scenarios, identifying risk areas and developing optimised maintenance plans in ways that minimise costs and maximise efficiency.

Remote sensing methods play an important role, allowing information on the scale of local communities to be obtained on a regular basis. The Sentinel and Landsat satellite systems provide access to spectral indices that reflect vegetation dynamics, moisture levels, surface temperatures and other parameters critical for analysing the state of territories. Sentinel-1 radar data allows for interferometric analysis of Earth's surface deformations with an accuracy of several millimetres, which is extremely important for communities affected by landslides, flooding or intensive development. The integration of satellite observation results into the municipal GIS creates a valuable information base for comprehensive spatial analysis, risk assessment, and management decisions in the field of land, environmental, and infrastructure management [135].

Comprehensive monitoring of the condition of territories and municipal facilities is becoming systematic thanks to the combination of geodetic data with the results of geoinformation analysis. Municipal GIS are the central link in the integration of multi-source information, providing the ability to combine laser scanning data, GNSS measurements, orthophoto plans, satellite images, sensor streams, and modelling results. This environment ensures a smooth transition from discrete measurements to a comprehensive assessment of territorial dynamics, which enhances the capabilities of local communities in terms of infrastructure management, territorial planning and ensuring resilience to external influences.

Geodetic solutions form the foundation of monitoring processes in territorial communities, as they ensure the spatial accuracy and metric reliability of information about the state of infrastructure objects and territories. Modern geodesy goes far beyond classical surveying and includes a set of methods focused on dynamic observation of spatial changes. GNSS technologies, terrestrial and mobile laser scanning, photogrammetry and remote sensing of the Earth allow the formation of multi-source datasets that reflect the state of the territory with high spatial and temporal

resolution. In municipal GIS, this data is used not only to record the current state, but also to analyse development trends and predict changes (fig. 5.4) [76].

Fig. 5.4 — Geodetic and GIS solutions as the basis for monitoring infrastructure and territories in local communities

A distinctive feature of geodetic monitoring of infrastructure is its focus on controlling the geometric parameters of objects and their changes over time. Buildings, structures, road surfaces, bridges, pipelines and other elements of engineering infrastructure are subject to operational loads, natural processes and material ageing. Even minor deformations or displacements can be indicators of potential emergencies. Systematic geodetic observations allow such changes to be detected at an early stage and form the information basis for preventive management decisions at the local community level.

The integration of geodetic data into municipal geoinformation systems provides the spatial context for infrastructure monitoring. The geometric parameters of objects are supplemented with attribute information about their functional purpose, technical condition, date of commissioning, and other characteristics. The result is a

comprehensive spatial-temporal model of the local community's infrastructure, which can be used for both operational management and strategic planning. It is at this stage that geodetic solutions acquire managerial significance, transforming from technical tools into a component of the decision support system.

GIS solutions for monitoring territories complement geodetic observations with the capabilities of spatial analysis and integration of diverse information sources. In municipal GIS, territory monitoring covers not only man-made infrastructure objects, but also natural components of the environment, in particular relief, hydrological network, soils, green spaces and water bodies. Spatial analysis allows identifying interrelationships between these components and assessing the impact of anthropogenic activity on the state of the territory. In this context, GIS acts as a tool for comprehensive analysis of territorial systems, which is critical for sustainable community development. [2].

One of the key areas of GIS monitoring is the control of land use and changes in land use. Local communities face problems of unauthorised construction, degradation of agricultural land, reduction of green areas and violations of environmental protection regimes. The use of satellite images, orthophoto plans and aerial photography results allows such changes to be quickly identified and integrated into municipal GIS. Geoinformation solutions provide the ability to perform comparative analysis of data for different time periods, which is the basis for assessing land use dynamics and making informed management decisions [4].

Monitoring of territories within municipal GIS also covers analysis of the environmental condition. Pollution of air, water bodies and soil, changes in microclimate and degradation of natural ecosystems have clear spatial localisation and dynamic nature. Geodetic data on relief and development, combined with environmental indicators, allow spatial models of pollution spread to be formed and environmental risks to the population to be assessed. In municipal management, such models are used to plan environmental protection measures and assess the effectiveness of the community's environmental policy.

An important aspect of geodetic and GIS solutions for monitoring territories is ensuring their spatial and temporal consistency. Data obtained from different sources may vary in accuracy, scale and frequency of updates. Municipal GIS serve as an integration environment within which such data is coordinated and a unified information space for monitoring is formed. This creates conditions for the use of intelligent analysis methods that require structured and coordinated geodata sets [81].

Thus, geodetic and GIS solutions for monitoring infrastructure and territories form the basic level of information support for municipal management. They ensure the acquisition of highly accurate spatial information, its integration and analytical processing, creating the basis for the further application of intelligent methods of analysis and forecasting.

The further development of geodetic and geoinformation solutions in municipal monitoring systems is associated with the transition from traditional observation and recording of changes to intelligent analysis of spatio-temporal processes. At this stage, artificial intelligence and machine learning methods play a key role, which are integrated into geoinformation systems and allow for the automation of pattern detection, change forecasting, and risk assessment. The intellectualisation of territory monitoring means a qualitative change in its functional purpose: from monitoring past conditions to supporting management decisions focused on the future development of territorial communities [4].

Intelligent monitoring methods are based on the use of large volumes of heterogeneous geodata obtained from geodetic measurements, remote sensing of the Earth, sensor networks and administrative sources. In this context, municipal GIS serve as an integration platform where data of different nature are brought into a single spatial and temporal environment. It is on this basis that machine learning algorithms can be applied, which require structured, consistent and representative data sets for correct training and functioning (fig. 5.5) [80].
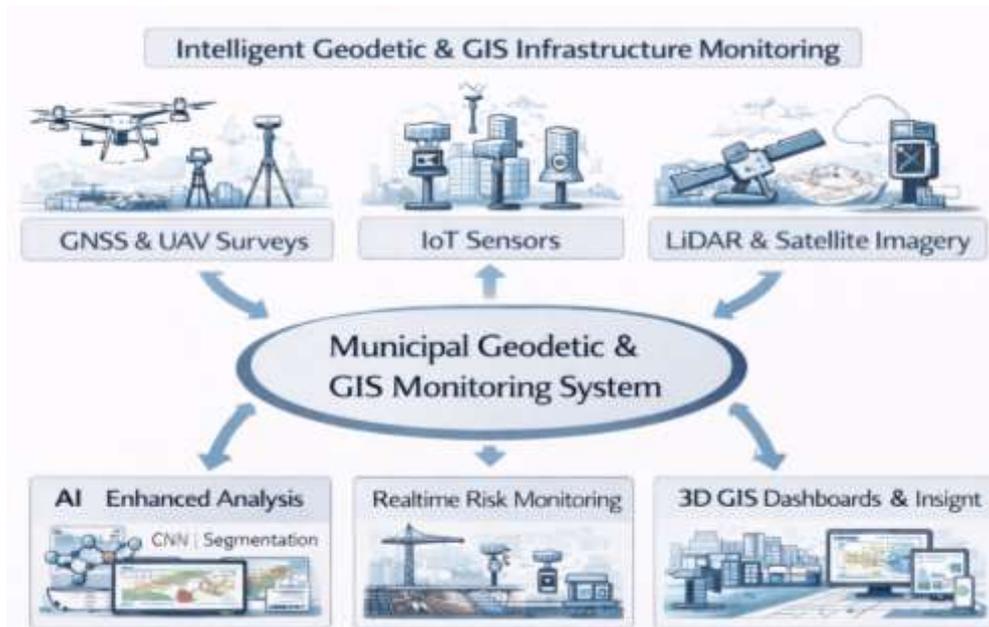
Fig. 5.5 — Intellectualisation of geodetic and GIS monitoring of infrastructure and territories in municipal systems

One of the most promising areas of intelligent monitoring is automated detection of changes in space. Comparing geodata collected over many hours allows changes in development, infrastructure condition, land use and the natural environment to be identified. Traditional methods of change analysis are based on comparing individual indicators or visual interpretation of images, which limits their scalability and speed. In contrast, the use of neural network models, in particular convolutional neural networks, allows for the automatic detection of spatial changes based on satellite images, orthophotomaps, and laser scanning data. In municipal management, such approaches are used to monitor illegal construction, infrastructure degradation, and changes in natural landscapes [136].

Intelligent GIS solutions enable a transition from simple detection of changes to their interpretation and prediction. Spatio-temporal models based on geodetic and GIS data allow for the analysis of infrastructure and territory development dynamics in the long term. For example, analysis of deformations in buildings and transport structures based on multi-hour geodetic observations combined with machine learning allows the probability of emergencies to be predicted. Such models create an information base for preventive infrastructure management and optimisation of maintenance costs [2].

Digital twins of territories and infrastructure objects play a special role in intelligent monitoring systems. In a municipal context, a digital twin is considered a dynamic spatio-temporal model that reflects the current state of the territory and allows for the simulation of its development scenarios. Geodetic data ensures the geometric accuracy of such models, while GIS and artificial intelligence methods are responsible for integration, analysis and forecasting. The use of digital twins in municipal management allows the consequences of management decisions to be assessed before they are actually implemented, which significantly reduces risks and increases planning efficiency [137].

Intelligent monitoring of territories is also widely used to analyse environmental processes and assess the state of the environment. Spatial models of pollution spread, changes in vegetation cover, soil degradation and water bodies can be built on the basis of geodata and supplemented with machine learning algorithms to predict environmental risks. In municipal GIS, such models are used to plan environmental protection measures, assess the impact of construction on the environment, and monitor compliance with environmental standards. Intelligent methods allow for complex nonlinear relationships between different environmental factors to be taken into account, which significantly increases the accuracy of the analysis [9].

An important aspect of intelligent monitoring is working with geodata streams that arrive in real time or near real time. Sensor networks, IoT devices, GNSS stations, and mobile platforms generate large amounts of data that require rapid processing and analysis. Integrating these streams into municipal GIS, combined with artificial intelligence algorithms, allows for the creation of real-time monitoring systems capable of responding to changes almost instantly. This is particularly relevant for monitoring traffic flows, the condition of utility networks, and environmental indicators in densely populated areas [138].

Thus, the intellectualisation of geodetic and GIS solutions for monitoring infrastructure and territories creates qualitatively new opportunities for municipal management. It ensures the transition from passive observation to active analysis and

forecasting, which is a necessary condition for the sustainable development of territorial communities.

The final dimension of geodetic and GIS solutions for monitoring infrastructure and territories in municipal management is related to the organisational, methodological and managerial conditions for their practical implementation. Even the most sophisticated technological solutions lose their effectiveness in the absence of adequate institutional support, regulated procedures and trained human resources. In this context, intelligent monitoring of territories should be considered as an element of a comprehensive territorial development management system that requires coordination of technical, organisational and regulatory components [9].

One of the key organisational prerequisites for the implementation of intelligent geodetic and GIS monitoring is the formation of a unified information space for the territorial community. In practice, data on infrastructure and territories are often stored in different structural units of local self-government bodies, used in different formats, and are not always mutually compatible. In this case, the municipal GIS acts as an integration platform that provides centralised access to geodata, its updating and sharing. Intelligent modules integrated into such a system allow for the automation of analysis and increased efficiency of management processes (fig. 5.6) [8].

*Fig. 5.6 — Organisational and managerial aspects of implementing intelligent
geodetic and GIS monitoring in local communities*

Methodological support for intelligent monitoring involves the development of standardised approaches to the collection, processing and analysis of geodata. Geodetic measurements, remote sensing materials and the results of sensor observations must meet specific requirements for accuracy, frequency and spatial consistency. Without clear methodological regulations, the results of intelligent analysis may be incorrectly interpreted or unsuitable for use in the management decision-making process. Therefore, an important component of GeoAI implementation in municipal GIS is the development of methodologies that define the rules for data preparation, model training parameters, and criteria for evaluating results [80].

The management aspect of implementing geodetic and GIS solutions for monitoring territories is related to incorporating the results of intellectual analysis into decision-making processes. This means that GeoAI outputs — risk maps, forecast scenarios, infrastructure status indicators — must be integrated into management regulations and used at various levels of management. It is important that the results of intelligent monitoring are understandable to managers and meet their practical needs. In this context, the visualisation of analysis results and their adaptation to management reporting formats plays an important role [2].

The reliability and interpretability of intelligent models used in municipal GIS deserve special attention. Machine learning algorithms can demonstrate high prediction accuracy, but their results are not always transparent to users. In municipal management, this creates risks of uncritical use of analysis results or distrust of them. Therefore, an important task is to combine intelligent methods with classical approaches to geodetic and GIS analysis, as well as to introduce mechanisms for model validation and explainability. This allows for a balance between automation of analysis and preservation of control by specialists.

Human resources are another critical factor for the successful implementation of intelligent territory monitoring. Modern municipal GIS require specialists with knowledge in the fields of geodesy, geoinformation technologies, and data analysis. Developing such competencies requires a systematic approach to training and upskilling local government staff. In this sense, the implementation of GeoAI in

municipal monitoring systems is closely linked to educational and scientific programmes aimed at developing digital and spatial competencies.

From a management perspective, intelligent geodetic and GIS monitoring facilitates the transition to a proactive model of territorial development management. Thanks to the predictive capabilities of GeoAI, local government bodies can not only respond to existing problems, but also plan measures to prevent them in advance. This is particularly important for infrastructure management, where the timely identification of potential risks reduces the cost of dealing with the consequences of accidents and increases public safety.

In conclusion, it should be noted that geodetic and GIS solutions for monitoring infrastructure and territories, combined with artificial intelligence methods, form a comprehensive information support system for municipal management. Their effectiveness is determined not only by technical characteristics, but also by the level of organisational readiness of territorial communities, the availability of methodological support, and the ability of management structures to use the results of intellectual analysis in practical activities.

5.3   Intellectual support for the processes of restoration and development of territorial communities

The processes of restoration and development of territorial communities in modern conditions are characterised by a high level of complexity, multifactoriality and significant spatial heterogeneity. The destruction of infrastructure, land degradation, disruption of transport and engineering networks, changes in land use patterns and socio-economic losses form a complex of interrelated problems, the solution of which requires a systematic approach. In such conditions, traditional planning and management methods based on fragmentary data and linear models prove to be insufficient. That is why intelligent processing of geodata and GeoAI methods are becoming a key tool for supporting the processes of restoration and development of territorial communities [2].

The restoration of territorial communities should be viewed not only as a process of rebuilding destroyed objects, but also as an opportunity to rethink the spatial organisation of the territory and form a new model for its development. Intellectual support for such processes involves the use of geodetic, geoinformation and analytical tools to assess the scale of losses, identify priority areas for restoration and model alternative development scenarios. In this context, GeoAI allows us to move from a reactive approach to proactive planning based on the analysis of spatial patterns and the prediction of the long-term consequences of management decisions (fig. 5.7) [4].

Fig. 5.7 — The role of intellectual processing of geodata in the processes of restoration and development of territorial communities

The methodological basis for intellectual support of recovery processes is the integration of multi-source geodata within municipal geoinformation systems. Geodetic measurement data, remote sensing materials, infrastructure inventory results, and socio-economic indicators form a unified spatio-temporal information space. On this basis, it is possible to apply machine learning algorithms capable of identifying hidden patterns, assessing the interrelationships between various factors, and forming predictive models of territorial development. This approach allows for the complex

nature of recovery processes, where spatial, economic, and social aspects are closely intertwined. [80].

An important component of intellectual support for recovery is spatial-analytical assessment of damage and losses. High-resolution satellite imagery, orthophoto plans, and laser scanning data allow for the rapid identification of destroyed or damaged infrastructure, assessment of land degradation, and changes in development. Integrating this data into municipal GIS systems, combined with intelligent classification and segmentation algorithms, enables automated assessment of the extent of damage. This significantly speeds up decision-making and allows for the development of informed recovery plans at an early stage [136].

Intellectual support for the recovery of local communities also involves analysing the spatial priority of measures. Not all areas require the same level of intervention, and community resources are usually limited. GeoAI allows the creation of spatial priority indices that take into account the degree of damage to infrastructure, the social significance of objects, the level of vulnerability of the population, and the potential for further development of the territory. Such indices are used to rank territories and objects, which allows for the optimisation of resource allocation and increases the effectiveness of recovery measures [81].

In the development of local communities, the intellectual processing of geodata provides support for strategic planning. The restoration of infrastructure and territories creates the conditions for modernising the spatial structure of communities, optimising land use and implementing the principles of sustainable development. GeoAI models allow for the assessment of the consequences of various development scenarios, particularly in terms of transport accessibility, environmental sustainability, and social inclusiveness. This makes it possible to formulate long-term development strategies that take into account both the current needs of the community and its prospects for economic growth (fig. 5.3) [137].

The socio-economic dimension of intellectual support for the restoration of territorial communities lies in the possibility of spatial analysis of demographic and social processes. Population migration, changes in the structure of employment, and

access to social infrastructure have a distinct spatial component. Integrating this data into municipal GIS, combined with smart analysis methods, allows for the assessment of the social consequences of management decisions and the adjustment of territorial development policies. Thus, GeoAI contributes to the formation of socially oriented strategies for community recovery and development.

In summary, it can be argued that intelligent support for the processes of restoration and development of territorial communities is forming a new methodology of municipal management based on spatial data, analytical modelling and forecasting. It allows a transition from fragmented and reactive approaches to systematic, adaptive management of territorial development.

The applied implementation of intellectual support for the processes of restoration and development of territorial communities is based on the use of spatial-analytical models capable of integrating heterogeneous geodata and transforming it into practically meaningful management scenarios. Post-crisis recovery of territories, regardless of the nature of the crisis factors, is always accompanied by a shortage of resources, limited time, and the need to make decisions in conditions of uncertainty. In such conditions, GeoAI becomes a tool for reducing uncertainty by forming alternative recovery scenarios, assessing their consequences, and supporting the selection of optimal management decisions [2].

One of the key application scenarios for intelligent geodata processing is spatial modelling of post-crisis infrastructure recovery. Geodetic data on the state of transport networks, engineering communications, housing stock and social infrastructure facilities are integrated into municipal GIS and supplemented with the results of remote sensing of the Earth. Based on this data, spatial damage models are formed, which serve as source information for intelligent algorithms for optimising recovery measures. Machine learning models allow analysing the relationships between the degree of damage, the functional significance of objects, and the potential socio-economic consequences of delays in restoration (fig. 5.8) [136].
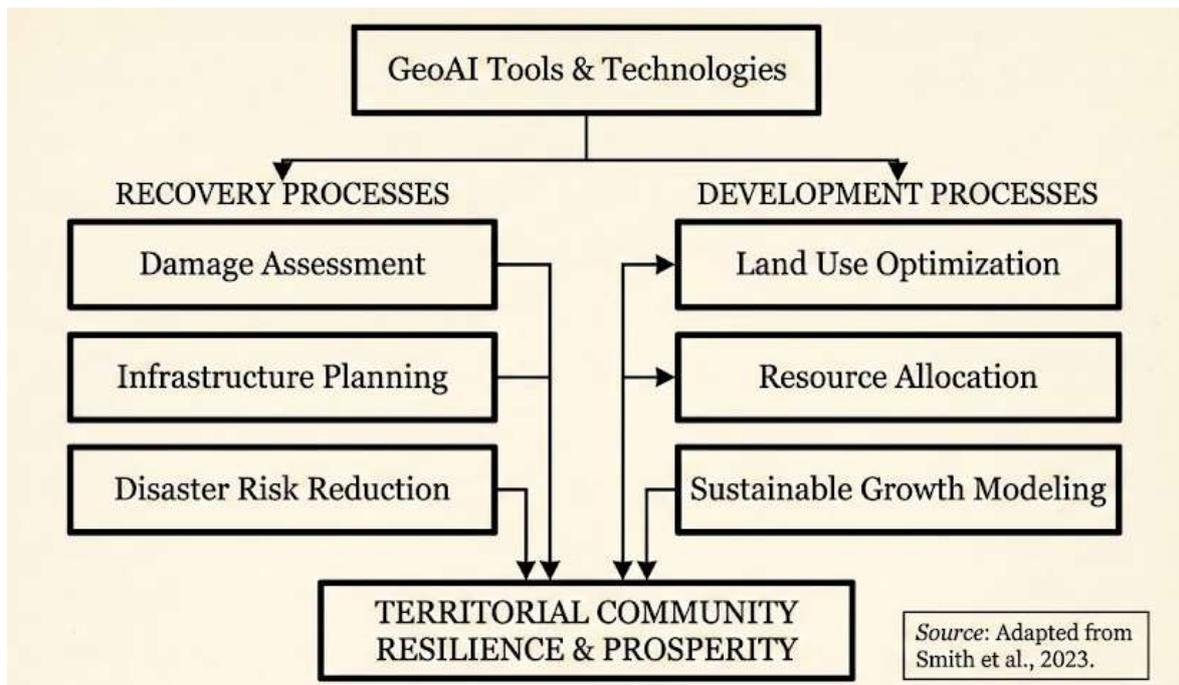
*Fig. 5.8 — Applied scenarios for using GeoAI in the processes of restoration and
development of territorial communities*

Prioritising restoration measures is another important applied aspect of intellectual support for the development of territorial communities. In real conditions, it is impossible to restore all infrastructure objects at once, so it is necessary to rank territories and projects according to their degree of importance. GeoAI allows the creation of multi-criteria spatial prioritisation models that take into account demographic indicators, the availability of social services, the economic activity of territories and the level of vulnerability of the population. Such models provide an objective basis for resource allocation and increase the transparency of management decisions [81].

In the development of territorial communities, GeoAI is used to model scenarios for spatial transformation of territories. Infrastructure restoration is often accompanied by changes in the functional use of land, redevelopment of transport corridors, and renewal of buildings. Intelligent geoinformation systems make it possible to assess the consequences of such changes in terms of transport accessibility, environmental sustainability, and social inclusiveness. This creates the opportunity to develop

scenarios that are focused not only on restoring the pre-war or pre-crisis state, but also on qualitatively improving the spatial organisation of the territory [137].

Intelligent support for recovery processes is also widely used in housing policy and housing stock restoration. Spatial analysis allows identifying areas with the greatest housing losses, assessing the needs of the population, and modelling options for temporary or permanent housing. Machine learning algorithms integrated into municipal GIS can be used to forecast housing demand, evaluate the effectiveness of different development models, and optimise land use in the process of rebuilding residential neighbourhoods.

An important application is the use of GeoAI to support the economic development of local communities in the post-crisis period. Spatial data on the location of enterprises, transport accessibility, labour resources and engineering infrastructure allow the creation of intelligent models of economic activity in territories. Based on such models, local authorities can identify priority investment areas, assess the potential for creating new jobs, and plan measures to restore the community's economy. In this context, GeoAI acts as a tool for strategic management of economic development [9].

Intellectual support plays a special role in the restoration of natural areas and ecosystems. Post-crisis transformations are often accompanied by the degradation of green areas, water bodies and soils. Intelligent geoinformation systems allow analysing the state of natural resources, assessing environmental risks and modelling scenarios for ecosystem restoration. This ensures the integration of environmental aspects into the overall development strategy of territorial communities and contributes to the implementation of sustainable development principles.

Thus, applied scenarios for the use of intelligent geodata processing in the processes of restoration and development of territorial communities cover a wide range of management tasks — from the restoration of infrastructure and housing stock to strategic planning of economic development and ecological rehabilitation of territories. GeoAI provides the ability to comprehensively analyse spatial processes and develop sound management scenarios, which is critically important in the post-crisis period.

The final dimension of intellectual support for the processes of restoration and development of territorial communities is related to the formation of sustainable institutional changes that determine the long-term trajectory of spatial, socio-economic and managerial development of territories. The use of GeoAI in municipal management is gradually transforming not only the tools of analysis and planning, but also the very principles of the organisation of management processes. In this context, the intellectual processing of geodata acts as a catalyst for the transition from fragmented and reactive management models to systematic, adaptive and evidence-based management of the development of territorial communities [2].

The institutional effects of GeoAI implementation are primarily manifested in the changing role of data in the municipal management system. Geodata ceases to be an auxiliary information resource and acquires the status of a strategic asset of the community. The creation of municipal geoinformation platforms with built-in intelligent modules contributes to the centralisation of data management, improving its quality and accessibility for various management departments. As a result, a single information space is created, within which decisions on the restoration and development of territories are made on the basis of coordinated and up-to-date spatial data (fig. 5.9) [8].

An important institutional consequence is the improvement of interagency coordination in the processes of restoration and development of territorial communities. Intellectual geoinformation systems provide shared access to the results of spatial analysis for local self-government bodies, municipal enterprises, planning and social services. This contributes to the coordination of management decisions in the areas of land use, infrastructure development, environmental policy and social protection of the population. In the long term, such coordination increases the effectiveness of community development strategies and reduces the risk of duplication or conflict between management measures.
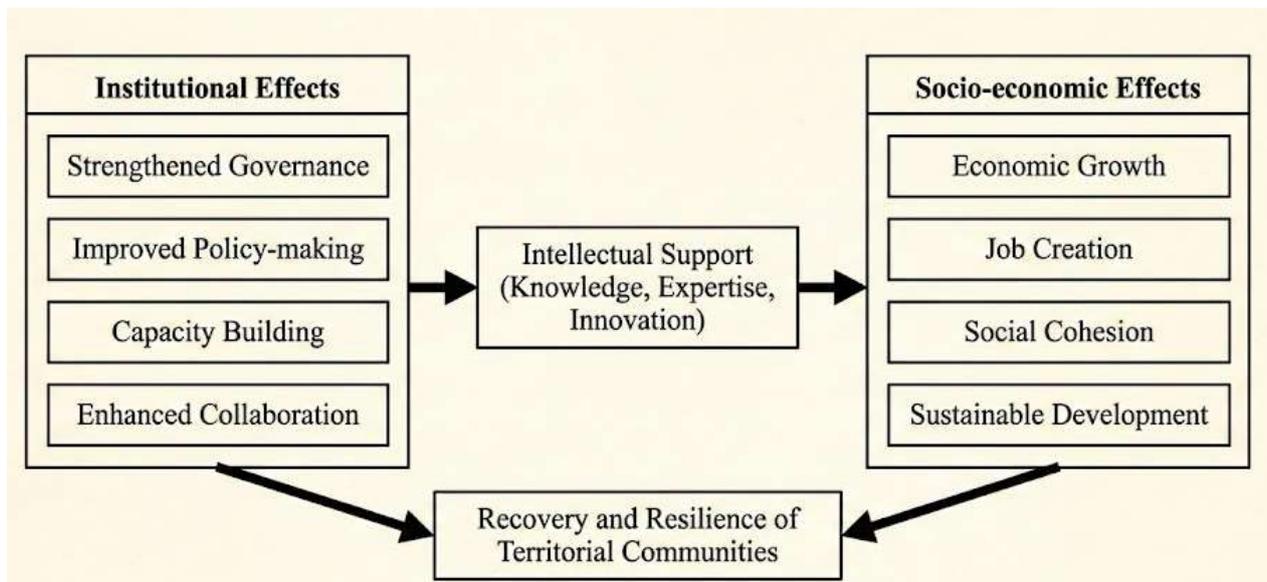
*Fig. 5.9 — Institutional and socio-economic effects of intellectual support for the
restoration and development of territorial communities*

The socio-economic effects of using intellectual support for the restoration of territorial communities are manifested in the increased targeting and fairness of management decisions. Spatial analysis allows for the uneven socio-economic development of territories, different levels of vulnerability of the population and access to infrastructure to be taken into account. GeoAI enables the formation of decisions focused on specific territories and population groups, which contributes to reducing social inequality and improving the quality of life in the community. In this regard, intelligent processing of geodata is a tool for implementing the principles of inclusive and sustainable development. [137].

The long-term economic effect of intellectual support for the development of territorial communities is associated with increased efficiency in the use of resources and reduced costs for eliminating the consequences of crises. GeoAI's forecasting capabilities allow for the timely identification of potential problems and the planning of preventive measures, which reduces financial losses and increases the investment attractiveness of territories. In addition, the use of intelligent geoinformation systems contributes to the formation of a favourable investment climate, as it ensures the transparency of spatial data and the soundness of management decisions.

The social dimension of the long-term effects of GeoAI lies in strengthening trust between local authorities and citizens. The visualisation of the results of intelligent analysis, open access to geodata and the opportunity to involve citizens in discussing development scenarios contribute to greater transparency in governance. This is particularly important in the process of rebuilding local communities, as public trust is a critical factor in the successful implementation of recovery programmes. In this context, intelligent GIS serve as a tool for communication and public participation.

The institutional and human resources aspect of intellectual support for the development of territorial communities is linked to the formation of new competencies in the field of spatial analytics and data management. The use of GeoAI requires specialists who are able to interpret the results of intelligent analysis and integrate them into decision-making processes. This necessitates the development of educational programmes and the improvement of the qualifications of local government employees. In the long term, this contributes to the institutional capacity of territorial communities and the formation of a data-driven management culture [80].

In strategic terms, intellectual support for the restoration and development of local communities creates the conditions for the formation of adaptive development strategies that can change in response to new challenges and opportunities. The combination of geodetic accuracy, geoinformation integration and intellectual analysis allows for the formation of development scenarios focused on the long-term sustainability of territories. This is particularly relevant in the context of climate change, urbanisation pressure and socio-economic instability, when traditional approaches to planning are losing their effectiveness.

In summary, it can be argued that intelligent support for the processes of restoration and development of territorial communities is one of the key factors in the formation of a new paradigm of municipal management. GeoAI provides the integration of spatial data, analytical modelling and management processes into a single system focused on sustainable development and improving the quality of life of the population.

5.4 Standardisation, interoperability and open geodata

Intelligent geodata processing systems in municipal management cannot function effectively without clearly defined principles of standardisation and interoperability. The growth in the volume of geospatial data, the diversity of its sources and the active use of GeoAI methods necessitate the creation of a unified regulatory and methodological environment that ensures data compatibility, correct integration and reproducibility of analysis results. In this context, standardisation and interoperability are not only technical requirements but also fundamental conditions for the sustainable development of municipal geoinformation systems [139].

Standardisation in the field of geodata involves the development of uniform approaches to the description, structuring, storage and exchange of spatial information. For municipal GIS, this means the unification of geodata models, coordinate systems, attribute schemes and metadata, which ensures the consistency of information between different local government departments and external information systems. In the absence of such standards, geodata remains fragmented, which significantly limits its reusability and integration into intelligent analytical models.

Interoperability, in turn, determines the ability of different information systems to exchange data and correctly interpret its content without additional transformations. This is critical in municipal management, as geodata is used in various functional areas, from land use and urban planning to infrastructure management, environmental monitoring, and social planning. Interoperable GIS allow these areas to be integrated into a single information and analytical system, which is a prerequisite for the application of GeoAI for comprehensive analysis of territories (fig. 5.10) [8].

Methodologically, standardisation and interoperability are based on the concept of the geodata life cycle, which covers the stages of collection, processing, storage, analysis and dissemination of information. At each of these stages, it is necessary to ensure compliance with defined standards, which guarantees the preservation of data quality and the possibility of its further use in intelligent systems. This is particularly important for GeoAI, as machine learning algorithms are sensitive to the quality and

structure of input data. Non-compliance with standards can lead to model training errors and incorrect management conclusions [80].
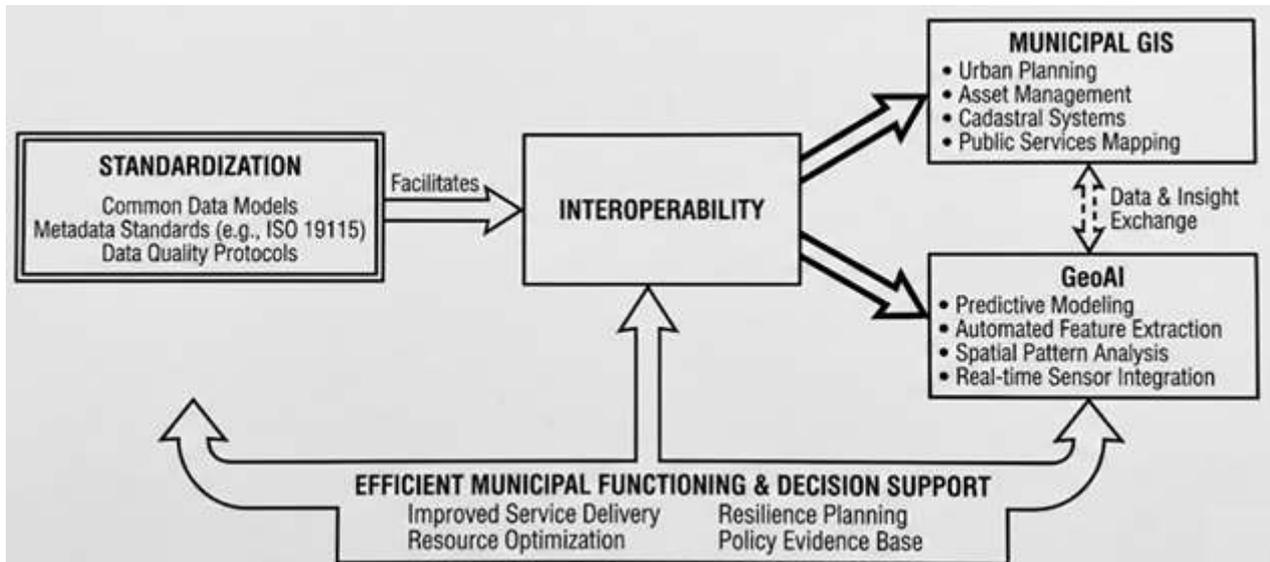

Fig. 5.10 — The role of standardisation and interoperability in the functioning of municipal GIS and GeoAI

In municipal GIS, geodata standardisation also serves to ensure the spatial integrity of management decisions. Different community departments may use data obtained at different times and with varying degrees of accuracy, creating the risk of spatial inconsistencies. Uniform standards for coordinate systems, accuracy and data updates minimise such risks and form a coordinated spatial vision for the development of the territory. This is particularly important in the processes of restoration and reconstruction of territories where spatial referencing errors can have significant socio-economic consequences.

An important aspect of standardisation is the formation of uniform approaches to metadata that describe the origin, quality and relevance of geodata. For municipal GIS, metadata is a key element of information resource management, as it allows the suitability of data for specific management tasks to be assessed. In the context of GeoAI, metadata plays an additional role, as it ensures the transparency of the processes of training and using intelligent models. The availability of structured

metadata allows the results of analysis to be reproduced and their reliability to be assessed [140].

Interoperability in municipal geoinformation systems has not only a technical but also a managerial dimension. It enables data exchange between different levels of government — local, regional and national. In the processes of restoration and development of territorial communities, this allows municipal data to be integrated with state cadastres, national geoinformation resources and international platforms. Such integration increases the completeness of the management information base and creates conditions for attracting foreign investment and international assistance [141].

In the context of intelligent geodata processing, interoperability takes on additional significance as a condition for the scalability of analytical solutions. GeoAI models developed for one territorial community can be adapted for other communities only if compatible data models and standards are used. This opens up opportunities for replicating best practices and creating national or regional platforms for intelligent analysis of territories. In the long term, this contributes to the formation of a unified digital space for territorial development management.

Therefore, standardisation and interoperability of geodata are basic conditions for the effective functioning of municipal GIS and the application of GeoAI in the management of territorial communities. They ensure the consistency, reproducibility and scalability of analytical solutions, which is critical for the processes of restoration and sustainable development of territories.

The technical implementation of standardisation and interoperability in municipal geographic information systems is based on the use of internationally recognised standards, data models and service-oriented architectures. The effective application of GeoAI in the management of territorial communities requires not only the availability of high-quality geodata, but also the ability to exchange, integrate and reuse it correctly between different information systems. That is why technical standards play a connecting role between different elements of municipal information infrastructure.

The specifications developed by the Open Geospatial Consortium, which define the rules for exchanging spatial data via network services, occupy a central place in the standardisation of geospatial services. The WMS, WFS, WCS and WMTS standards provide unified access to cartographic images, vector and raster data regardless of platform or software. For municipal GIS, this means the ability to integrate data from various sources — cadastral systems, urban planning registers, infrastructure monitoring systems — into a single environment without the need for complex transformations (fig. 5.11) [142].
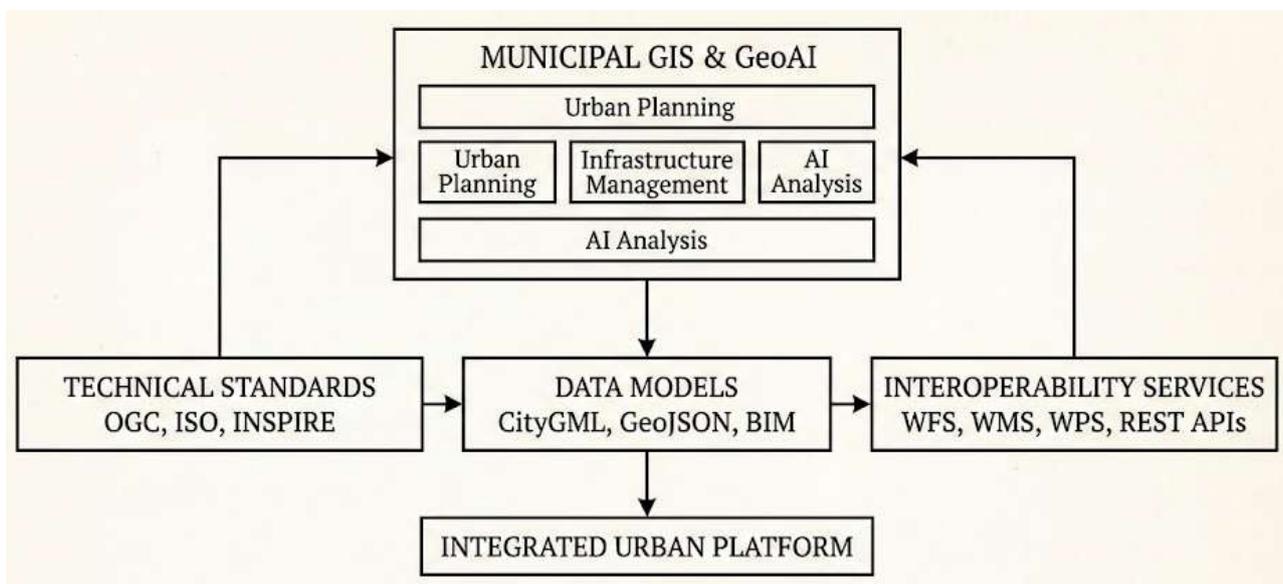

Fig. 5.11 — Technical standards, data models and interoperability services in municipal GIS and GeoAI

Services providing access to vector data are particularly important for GeoAI, especially WFS and API Features standards, which allow structured geodata to be obtained for further analysis and training of intelligent models. The use of standardised access services ensures the reproducibility of analysis results and simplifies the integration of machine learning algorithms into municipal GIS. This creates the technical prerequisites for building scalable GeoAI pipelines capable of working with data from different territorial communities.

An important component of standardisation is the use of the ISO 191xx series of standards developed by the International Organisation for Standardisation for

geographic information. The ISO 19107, ISO 19109 and ISO 19110 standards define the rules for the spatial description of objects, their classification and cataloguing, which is critical for building consistent data models in municipal GIS. The application of these standards allows the formation of unified catalogues of infrastructure objects and territories, which can be used as a basis for intelligent analysis [143].

Data models play a key role in ensuring interoperability, as they determine the semantic consistency of geodata. Object-oriented models are widely used in municipal GIS, allowing infrastructure objects, land plots and building elements to be described taking into account their spatial and functional characteristics. The use of standard data models simplifies the integration of information from different sources and creates the conditions for the use of unified intelligent analysis models in different territories.

Spatial databases, in particular PostgreSQL/PostGIS-based solutions that support OGC standards and ensure efficient storage and processing of geodata, play a significant role in the practical implementation of interoperability. In municipal GIS, such databases serve as a central repository of spatial information accessible to various services and analytical modules. The integration of GeoAI with spatial databases allows geodata to be used directly in the processes of training and applying intelligent models, while maintaining the semantic and spatial consistency of the data. [144].

Special attention should be paid to metadata exchange standards and practices that ensure transparency and manageability of geodata. The ISO 19115 standard defines the structure of metadata describing the origin, quality, and relevance of geodata. In municipal GIS, metadata plays a key role in selecting data for specific management tasks and training GeoAI models. The availability of standardised metadata allows you to assess the suitability of data for analysis and avoid using outdated or incorrect information. [140].

Technical aspects of interoperability also include the use of service-oriented and microservice architectures, which enable flexible integration of various components of municipal GIS. In such architectures, geodata, analytical modules, and visualisation services function as independent but interconnected components. This allows for the

gradual implementation of intelligent GeoAI modules without the need for a complete overhaul of the existing information infrastructure of the local community.

The practice of implementing interoperability in municipal GIS shows that technical standards must be accompanied by organisational regulations for their application. Defining responsibilities for maintaining standards, data quality control, and service updates is a prerequisite for stable system operation. Combined with technical standards, such regulations ensure the long-term viability of municipal geoinformation systems and create a basis for scaling GeoAI solutions.

Thus, technical standards, data models, and services are key tools for implementing interoperability in municipal GIS. They ensure the consistency of geodata, the reproducibility of analysis results, and the scalability of intelligent solutions.

The final element of the standardisation and interoperability system in municipal geoinformation systems is the concept of open geodata, which significantly expands the functional capabilities of territorial development management. Open geodata is seen not only as a tool for transparency in local government, but also as a strategic resource that ensures the innovative development of territorial communities, stimulates the use of GeoAI, and contributes to the formation of open data ecosystems. In today's environment, it is the openness and accessibility of geospatial information that are becoming the determining factors in the effectiveness of intellectual data processing [7].

Open geodata in municipal administration covers a wide range of information, from data on the boundaries of administrative-territorial units, land use and infrastructure to the results of environmental monitoring, transport flows and socio-economic indicators. Provided that interoperability standards and principles are followed, such data can be reused by various users, including government agencies, scientific institutions, businesses and the public. For GeoAI, this creates an expanded learning environment in which intelligent models can be formed based on representative and diverse sets of geodata (fig. 5.12) [145].
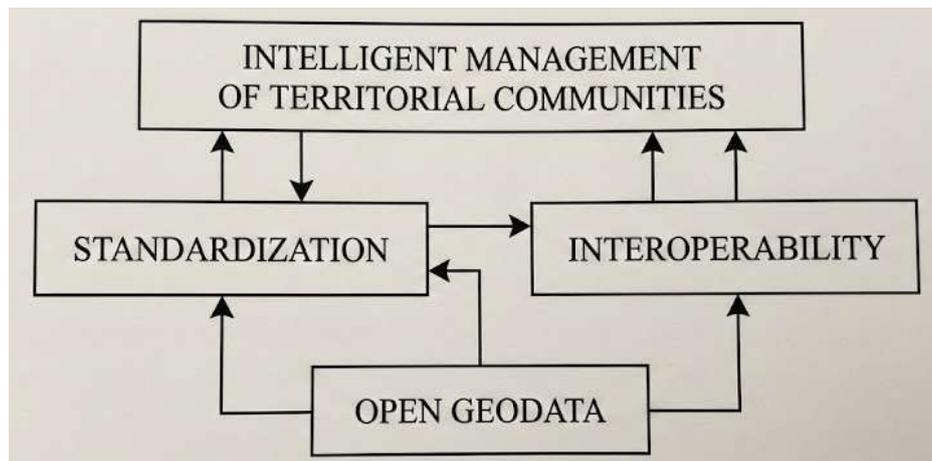
Fig. 5.12 — The role of open geodata in the system of standardisation, interoperability and intelligent management of territorial communities

The management effect of using open geodata is manifested in increased transparency and accountability of local self-government bodies. Public access to spatial information about the state of territories, the implementation of infrastructure projects and the use of budget resources creates conditions for public control and reduces the risks of making unfounded management decisions. In combination with intelligent analytical tools, open geodata allows not only to visualise the current state of the territory, but also to demonstrate forecast scenarios for its development, which increases the level of trust between the authorities and the community.

An important aspect is the role of open geodata in shaping the innovative environment of territorial communities. The availability of standardised geodata stimulates the development of new services and applications based on it, including solutions in the field of transport planning, environmental monitoring, property management and spatial analytics. In this context, GeoAI acts as a tool for transforming open data into knowledge and management insights that can be used for strategic decision-making. Thus, open geodata contributes to the development of the digital economy and increases the competitiveness of local communities [146].

From a standardisation perspective, open geodata must meet specific requirements regarding formats, metadata and access services. The absence of such requirements leads to fragmentation of open datasets and limits their use in intelligent analysis systems. Therefore, combining open data policies with interoperability

standards is critical for the effective use of GeoAI in municipal management. Only standardised open geodata can be directly integrated into geoinformation and analytical platforms without additional costs for their preparation [141].

The social impact of open geodata lies in expanding opportunities for public participation in spatial planning and development processes. Open municipal geoportals, interactive maps, and dashboards allow citizens to access up-to-date spatial information and participate in discussions on strategic decisions. Combined with intelligent analysis tools, this creates conditions for the formation of collective knowledge and improves the quality of management decisions by involving a wide range of stakeholders.

The long-term effect of using open geodata in combination with GeoAI is manifested in the formation of open data as an institutional norm of municipal management. Territorial communities that systematically implement open geodata policies benefit from increased investment attractiveness, more effective development planning, and better integration into national and international information spaces. In the long term, this contributes to the formation of a unified digital space for territorial management, within which GeoAI can be used as a universal tool for analysis and forecasting.

In summary, it can be argued that open geodata is an integral part of the standardisation and interoperability system in municipal GIS. It ensures the accessibility and reuse of spatial information, creates conditions for innovation, and increases the efficiency of territorial community management. In combination with standards and interoperable services, open geodata forms the information basis for the widespread implementation of GeoAI and the transition to data-driven territorial development management.

5.5   Prospects for scientific research and educational application of results

The current stage of development of municipal geographic information systems is characterised by a gradual transition from traditional methods of spatial analysis to

complex intelligent approaches based on the use of machine learning methods, deep neural networks and big data geanalytics. In this context, GeoAI is emerging as an interdisciplinary scientific field that integrates the achievements of geodesy, geoinformatics, computer science, applied mathematics, and data science. Prospects for further scientific research in this area are directly related to the development of municipal GIS as intelligent decision support systems capable of adapting to the dynamic conditions of territorial development. [147].

One of the key scientific areas for further research is the development of methods for integrating heterogeneous geodata within a single analytical environment. Municipal GIS operate with data obtained from various sources — the results of geodetic measurements, remote sensing of the Earth, sensor networks, cadastral registers, and socio-economic statistics. Each of these types of data has its own spatial, temporal, and semantic characteristics, which complicates their joint analysis. Further scientific research should be aimed at creating universal models for presenting geodata that allow for the correct combination of different scales, levels of accuracy, and information formats within GeoAI pipelines (fig. 5.13) [50].
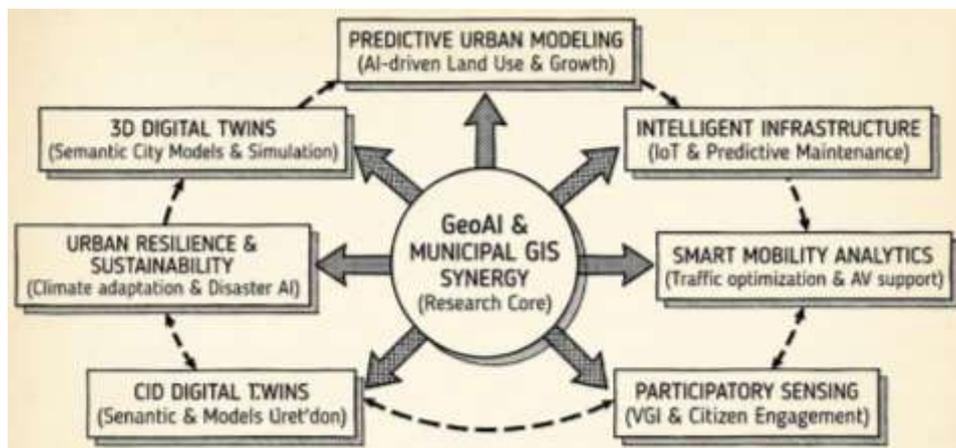

Fig. 5.13 — Key areas of promising scientific research in the field of GeoAI and municipal GIS

A promising area of scientific research is the development of spatially oriented machine learning models that take into account the topological, metric, and semantic properties of geographic space. Unlike classical data analysis algorithms, GeoAI

models must adapt to the specifics of spatial information, in particular to spatial autocorrelation, heterogeneity of object distribution, and scale dependence of phenomena. The further development of graph neural networks, spatio-temporal models, and hybrid approaches opens up new opportunities for analysing territorial development processes, forecasting land use changes, and assessing the impact of management decisions on the spatial structure of communities [112].

The issues of explainability and interpretability of intellectual models used in municipal GIS require separate scientific study. It is important for local authorities not only to obtain a forecast or analytical result, but also to understand the logic behind its formation. This necessitates the development of explainable AI (XAI) methods adapted to spatial data and management tasks. Further research in this area should contribute to increasing trust in GeoAI solutions and expanding their practical application in municipal management [149].

Research related to scaling intelligent models in space and time is also scientifically significant. Most existing GeoAI solutions are focused on analysing individual territories or local tasks. However, for municipal GIS, it is important to create models that can be adapted to different territorial communities, taking into account their individual characteristics. This requires the development of knowledge transfer, transfer learning, and federative learning methods that allow the experience of some communities to be used to improve management efficiency in others [150].

In the context of sustainable territorial development, a promising scientific direction is the combination of GeoAI with models for assessing environmental and socio-economic risks. Intelligent processing of geodata allows for the formation of comprehensive indicators of the state of territories, taking into account the spatial interaction of natural and anthropogenic factors. Further research in this area should be aimed at developing integrated models capable of supporting strategic decision-making in the areas of territorial planning, infrastructure restoration and adaptation to climate change.

Thus, the prospects for scientific research in the field of intelligent geodata processing in municipal GIS are linked to the deepening of interdisciplinary

integration, the development of specialised spatial machine learning models, and the increased transparency and scalability of GeoAI solutions.

One of the key aspects of the development of intelligent geographic information systems in municipal management is the integration of GeoAI research results into the professional education system. The educational dimension appears as a natural continuation of scientific research and as a necessary condition for the sustainable use of intelligent technologies in the practice of territorial communities. In the context of the digital transformation of public administration, the reform of urban planning legislation and the modernisation of the public administration system, there is a growing need for specialists who are not only able to work with geodata, but also to design, implement and explain intelligent analytical solutions. Therefore, the educational application of GeoAI results goes beyond training and short courses — it includes the modernisation of university programmes, the development of new competency models, the creation of educational and scientific laboratories, and the integration of real municipal tasks into the educational process (fig. 5.14) [151].
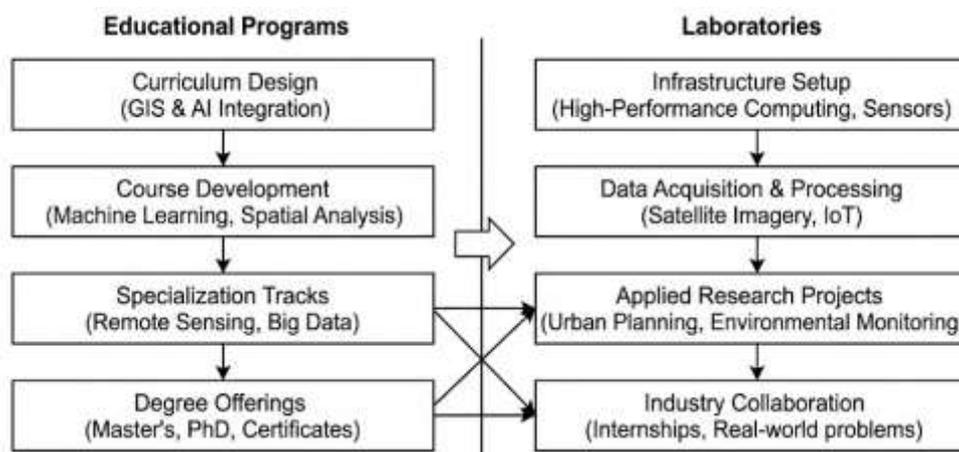
Fig. 5.14 — Development of educational programmes and laboratories for training specialists in the field of GeoAI

First and foremost, the development of GeoAI requires a rethinking of traditional approaches to teaching geodesy, geoinformatics, and land management. For a long time, educational programmes have focused primarily on mastering GIS tools, digital cartography technologies, and spatial analysis methods. However, modern analytical

systems require students to develop the ability to work with large amounts of data, apply machine learning methods, build geo-analytical pipelines, and develop intelligent services for municipal management systems. In this context, it is necessary to integrate modules on data science, artificial intelligence, and spatial statistics into educational programmes in specialities such as 193 'Geodesy and Land Management,' 103 'Earth Sciences,' 122 'Computer Sciences,' 126 'Information Systems and Technologies,' etc [152].

There is a growing need to develop training courses and modules focused on the practical application of GeoAI in engineering, urban planning, environmental and management activities of local communities. Such modules may include: 'Fundamentals of Neural Network Analysis of Geodata,' 'Deep Learning for Remote Sensing,' 'Spatio-Temporal Models in Risk Management,' 'Intelligent Urban Monitoring Services,' and 'GeoAI for Municipal Management.' The creation of such courses requires an interdisciplinary approach, with geodesy and land management teachers collaborating with specialists in machine learning, software engineering, statistics, and management.

Practical classes that simulate real situations faced by local communities require special attention: forecasting transport loads, identifying flood risks, analysing land use changes, assessing the condition of engineering networks, and optimising public transport routes. The use of GeoAI in these tasks allows students not only to master technical skills, but also to understand the essence of the management processes behind the data. This creates a generation of specialists capable of thinking at the intersection of technological and managerial contexts.

An important educational trend is the use of real geodata sets, open geoportals, and municipal information systems as training laboratories. Platforms such as ArcGIS Online, Copernicus Open Access Hub, Sentinel Hub, OpenStreetMap, and GeoNode are becoming the main tools for training students to work with spatial information. They allow students to practise their skills in processing satellite data, modelling spatial processes, and integrating heterogeneous data into the GeoAI pipeline. The use of open sources is particularly important for developing reproducible research competencies —

the ability to repeat scientific experiments and analyses based on standardised and publicly available data [153].

The educational component of GeoAI implementation in the learning process also includes the creation of specialised educational and scientific laboratories that combine the functions of an educational environment, a research centre, and an innovation platform for young scientists. Such laboratories should provide access to powerful geocomputing resources, machine learning tools, cloud services, spatial databases, and modelling software products. In this context, laboratories for remote sensing data analysis, object recognition in satellite images, 3D modelling and visualisation, and intelligent analysis of urban infrastructure are particularly relevant.

The creation of such laboratories contributes to the training of a new type of specialist — analysts capable of working with large amounts of spatial information, building machine learning models, and integrating analysis results into decision-making processes. In addition, educational and scientific laboratories are becoming a platform for cooperation between universities, local communities, and industrial partners, which contributes to the formation of innovative ecosystems on a regional scale.

Equally important is the issue of developing new competencies among teachers, who must be proficient in modern methods of geodata analysis and machine-oriented spatial modelling tools. The professional development of teaching staff, participation in international seminars, training courses, academic mobility programmes and professional networks is becoming a key factor in the modernisation of the geoinformation education system. Pedagogical models should take into account the principle of 'learning by doing', a focus on project activities and the use of real-life cases of territorial management.

The integration of GeoAI into postgraduate education and the professional development system for local government employees opens up significant prospects. Targeted professional development programmes may include training in geodata processing, remote sensing data analysis, the application of AI in infrastructure management, risk forecasting and the use of open geodata in decision-making. This

allows for the creation of a unified professional space within which specialists from different community departments share common terminology, tools, and analysis methods.

The educational transformation aimed at implementing GeoAI also has a profound strategic dimension. In the long term, it allows for the creation of a continuous learning environment in which specialists can constantly update their skills in line with the dynamics of technological development. Such a system ensures the sustainability of municipal GIS, increases management efficiency and creates intellectual conditions for the development of territorial communities.

In summary, it can be argued that the integration of GeoAI research results into the education system is a key condition for the transition to intelligent municipal management. The educational component complements the scientific and managerial dimensions of GeoAI, forming a holistic ecosystem of knowledge, technologies and competencies.

The strategic prospects for the development of intelligent geodata processing in municipal geoinformation systems determine the further evolution of digital territory management and the formation of a new generation of intelligent services. The final section of this subsection summarises the scientific, technological, social and managerial trends that shape the future of GeoAI, defining its role as the core of modern municipal GIS. These prospects integrate the results of the previous parts of the section, forming a long-term vision for the implementation and use of intelligent technologies at the level of territorial communities.

The first key trend is the formation of full-fledged digital twins of territorial communities. In the coming years, digital twins will become a fundamental platform for strategic planning, engineering infrastructure development modelling, risk analysis and communication with citizens. Unlike traditional GIS, digital twins combine geodata, streaming sensor data, mobility data, and engineering models in a single interactive environment. GeoAI is at the core of such systems, providing automatic updates, forecasting, and real-time analytical support for decisions [56].

For municipal GIS, this means a transition to a new management paradigm in which intelligent algorithms predict infrastructure loads, model accident scenarios, optimise traffic flow, warn of critical network conditions and enable reconstruction planning. In this context, GeoAI becomes not just an analysis tool, but a platform for implementing the concept of a 'learning city system' (fig. 5.15)
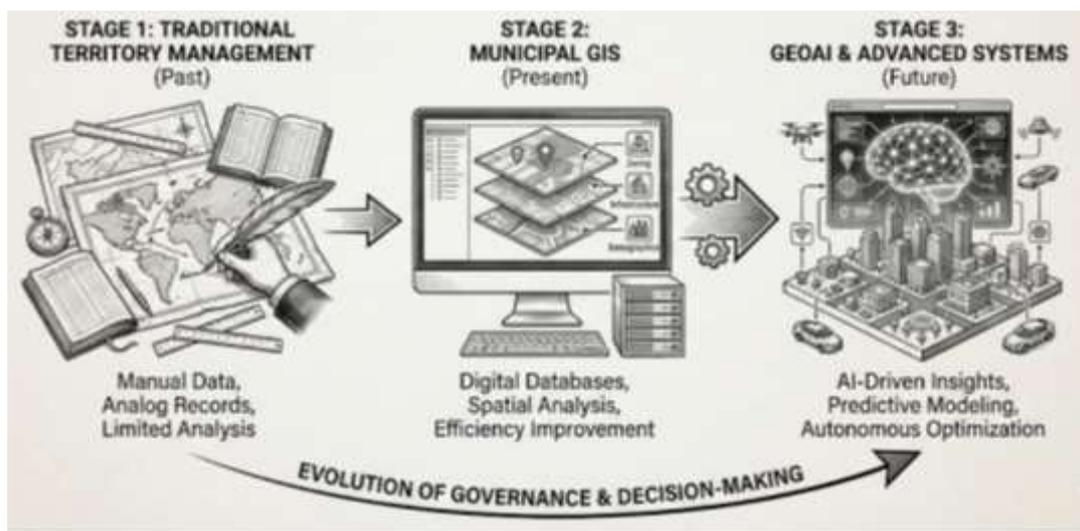

Fig. 5.15 — Strategic prospects for the development of municipal GIS and GeoAI as an evolution of territory management

The second prospect is the complete automation of geospatial workflows in municipal management. The use of GeoAI algorithms will enable the creation of automated geodata processing pipelines that will include automatic classification of satellite images, object selection, change analysis, construction of spatial risk indices, and preparation of analytical reports. This will significantly reduce the dependence of local communities on manual labour by analysts and increase the efficiency of management decisions. Decision-making will be largely based on recommendations from intelligent systems, ensuring the effective allocation of community resources and the formation of adaptive development strategies [154].

The third trend is the deepening integration of GeoAI with cloud and edge technologies. As streaming data from IoT sensors, video cameras, engineering systems, and telemetry platforms develops, computing will increasingly be performed closer to the data source (edge computing). This will allow municipal GIS to obtain analytical results almost instantly, without delays in transferring large amounts of data to central

servers. Edge analysis will become particularly important for managing transport, energy systems, water supply, heating networks, and security systems. In this case, GeoAI will function as a multi-layered intelligent system capable of autonomous decision-making at various levels of infrastructure [155].

The fourth perspective is the development of citizen participation systems based on spatial data and intelligent platforms. The spread of mobile applications, crowdsourcing tools and smart portals will allow citizens to participate in assessing the state of territories, identifying problems, monitoring infrastructure, eco-monitoring and evaluating the quality of services. GeoAI in such systems will act as an automatic aggregator, classifier, and validation mechanism. This will contribute to the formation of a new type of territorial communities — digital, responsible, and included in co-governance processes. Such a transformation correlates with global trends in open government and digital democracy [156].

The fifth strategic perspective is the creation of a unified national space for intelligent analysis of geodata, which will combine the digital solutions of local communities, regional management systems, state cadastres and industry registers. Such an integrated space will allow for the effective use of data from various agencies to monitor the state of the country, analyse risks, optimise land resources, manage engineering infrastructure, and ensure security. GeoAI will act as the data integrator and analytical core of such a platform, providing:

- unified analysis models;

- standardised approaches to risk assessment;

- scalable forecasting methods;

- increased accuracy of management decisions.

This will not only improve the efficiency of municipal management, but also ensure the strategic development of the state as a whole, based on data, analytics and modelling.

The sixth trend is the transformation of approaches to impact assessment and validation of intelligent models. Further research should focus on developing methods for ethical, legal and technical control over GeoAI algorithms. In particular, the

following areas will be important:

- assessment of algorithm transparency;

- managing the risks of algorithmic errors;

- ensuring the non-discriminatory nature of models;

- standardising GeoAI testing and certification procedures.

Such approaches are already being actively developed in the EU, the US and Canada and will soon form the basis of the regulatory environment for intelligent geoinformation technologies [157].

The seventh perspective is the development of the humanitarian dimension of GeoAI, which aims to study the social effects of the digital transformation of territories. Geographers, urbanists, sociologists and economists will investigate:

- the impact of intelligent systems on inequality of access to services;

- changes in the spatial organisation of cities under the influence of algorithms;

- the transformation of the labour market;

- new models of interaction between authorities and citizens;

- the formation of digital communities.

This direction combines social sciences and geoinformation technologies, forming a whole new class of research — GeoAI & Society [158].

To sum up, it can be argued that intelligent processing of geodata in municipal GIS has significant potential to transform not only the technical aspects of territorial management, but also the organisational, social, economic and cultural foundations of the functioning of territorial communities. GeoAI is becoming a strategic driver of development, combining analytics, modelling, forecasting and communication.

In the strategic perspective, municipal GIS will perform the following functions:

- be a platform for interactive management and monitoring;

- provide automated assessment of the state of territories;

- support decision-making based on predictive models;

- serve as a tool for education and research;

- act as a centre for digital interaction between the community, business and government.

CONCLUSIONS

As a result of the research presented in the monograph, a comprehensive analysis of the role of geodetic and geospatial data in digital municipal management systems was carried out, their conceptual significance was substantiated, quality issues were identified, and scientific and methodological foundations for their intellectual processing using modern artificial intelligence technologies were formed. The work carried out has made it possible to form a holistic view of the theoretical, methodological and applied aspects of the use of geodata in new-generation municipal geoinformation systems, which are being formed in the context of the digital transformation of territorial management.

The monograph proves that geodetic and geospatial data are a strategic resource for modern territorial communities, as they provide a spatial basis for the implementation of management functions, territorial development planning, land use control, management of engineering and transport infrastructure, environmental status, etc. It has been established that traditional approaches to processing such data no longer meet the requirements of a dynamic urban environment, in which the relevance of information, the ability to model changes over time, and the possibility of integrating heterogeneous sources into a single information environment play an important role. It has been determined that geodata is the conceptual core of the transition to digital twins of territories, scenario modelling, intelligent analysis of urban development processes and the functioning of Smart City platforms.

The study has made it possible to systematise the sources of geodetic and geospatial data formation in municipal systems: from classical geodetic measurements (GNSS, tacheometry, levelling) to remote sensing data, LiDAR scanning, IoT sensors, cadastral and registry systems, and open geospatial platforms. It has been shown that the multi-source nature of information not only creates potential for comprehensive analysis, but also gives rise to a number of problems: from significant differences in data quality and structure to difficulties in integrating and harmonising spatial layers. It has been established that important factors in the quality of geodata are accuracy,

completeness, relevance, and logical consistency, and that violations of these factors lead to the accumulation of errors, distortion of spatial analysis results, and reduced effectiveness of management decisions.

It has been scientifically proven that preliminary desk processing of geodetic information — noise filtering, coordinate transformation, normalization of indicators, topological control, formation of training samples — is important for the further application of artificial intelligence methods. It has been proven that the effectiveness of machine learning models in the field of spatial analysis directly depends on the quality of the initial geodata; therefore, intelligent technologies cannot be considered in isolation from geodetic processes, but must be integrated into a single geoanalytical pipeline.

The results of the monograph show that artificial intelligence methods — in particular CNN, GNN, LSTM, ConvLSTM, algorithms for segmentation, classification, forecasting and reconstruction of geospatial objects — open up new opportunities for automating spatial analysis, monitoring the urban environment and supporting decision-making in local communities. It has been substantiated that the use of such models allows moving from static cartographic solutions to adaptive, predictive and situation-oriented systems capable of analysing the dynamics of transport flows, development of buildings, changes in engineering loads, environmental conditions and structural characteristics of urban processes. Particular attention is focused on the possibilities of integrating GeoAI technologies into digital terrain models, transport and engineering networks, environmental monitoring and risk assessment systems.

The paper proposes a conceptual architecture for an intelligent municipal GIS, which includes modules for data collection, pre-processing, analytical modelling based on neural networks, IoT stream data processing, interoperable exchange mechanisms based on OGC standards, as well as interactive Smart City Dashboard systems for visualisation and management decision support. It is shown that the use of cloud technologies, edge AI, microservice architectures and digital twins allows for the implementation of adaptive, scalable and highly productive GeoAI solutions for local communities.

The results confirm that intelligent processing of geodata can be a tool for ensuring not only effective management but also social justice, as it allows for the identification of uneven access to services, violations in land use, environmental threats, illegal construction, degradation of green areas, and other critical problems in the urban environment. It has been proven that the combination of spatial models, neural networks and open data creates the basis for transparent, scientifically sound and socially oriented territorial management.

Thus, the results of the monograph confirm that the introduction of intelligent methods for processing geospatial and geodetic data into the structure of municipal geoinformation systems is a necessary condition for the modern digital transformation of territorial communities. The proposed methodology, architectural solutions, system models and analytical approaches can be used as a basis for creating comprehensive next-generation intelligent GIS capable of improving the quality of management decisions, the efficiency of infrastructure development, the sustainability of territories and the formation of Smart City ecosystems adapted to the needs of communities and the requirements of the digital age.

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APPENDICES

Appendix A. ETL process algorithms for preliminary processing of geodata

Appendix A.1. Generalised ETL process algorithm:

Input: set of raw geospatial data D = {D1, D2, ..., Dn}

Output: standardised set of geodata S in a single coordinate system and structure

1. Environment initialisation:

    1.1. Set the target coordinate system CRS_target

    1.2. Define the attribute schema and classification reference books

    1.3. Set quality control parameters (RMSE_max, topology rules)

2. Extract stage:

    2.1. For each source Di, perform:

        – check availability

        – read metadata

        – load geometry and attributes into temporary storage

3. Transform stage:

    3.1. For each layer, perform the following:

        – transform the coordinate system to CRS_target

        – normalise attributes according to a single schema

        – perform geometric cleaning (elimination of self-intersections, gaps)

        – apply topological rules (neighbourhood, adjacency, network integrity)

        – perform statistical accuracy control (RMSE, comparison with control points)

        – mark or reject objects that do not meet the quality criteria

4. Load stage:

    4.1. Load cleaned and validated data into the target GIS/DB:

       – record in spatial DBMS (PostGIS) or corporate GIS

       – update metadata (date, responsible person, source, version)

5. Reporting:

    5.1. Generate a log of execution with a description of errors, statistics, rejected objects

    5.2. Save the ETL process configuration for reuse

End.

Appendix B. Python scripts for automating vector and raster data processing

Appendix B.1. Example Python script for automated conversion, cleaning, and saving of vector layers

```python
import geopandas as gpd
from shapely.ops import unary_union
from pathlib import Path

# Input directory with raw layers
input_dir = Path(r'D:\GIS_DATA\raw_vectors')
# Output GeoPackage
output_gpkg = Path(r'D:\GIS_DATA\processed\municipal_data.gpkg')
# Target coordinate system (e.g., USK-2000 / local EPSG)
TARGET_CRS = 'EPSG:5561'

def clean_geometry(gdf: gpd.GeoDataFrame) -> gpd.GeoDataFrame:
    # Removal of invalid geometry
    gdf['geometry'] = gdf['geometry'].buffer(0)
    # Filtering empty geometry
    gdf = gdf[~gdf.geometry.is_empty & gdf.geometry.notnull()]
    return gdf

def process_layer(path: Path, layer_name: str):
    print(f'Processing layer: {layer_name}')
    gdf = gpd.read_file(path)

    # Transformation to target coordinate system
    if gdf.crs is not None and gdf.crs != TARGET_CRS:
        gdf = gdf.to_crs(TARGET_CRS)
```

```python
    elif gdf.crs is None:
        # If CRS is missing – log or force setting
        print(f'Attention: CRS is missing in {layer_name}, set it manually!')
        # gdf.set_crs(TARGET_CRS, inplace=True)

    # Geometric cleaning
    gdf = clean_geometry(gdf)

    # Minimal attribute normalisation (example)
    gdf.columns = [c.strip().lower() for c in gdf.columns]

    # Writing to GeoPackage (each layer is a separate table by name)
    gdf.to_file(output_gpkg, layer=layer_name, driver="GPKG")

if __name__ == '__main__':
    for shp in input_dir.glob('*.shp'):
        layer = shp.stem
        process_layer(shp, layer)
```

Appendix B.2. Example of a Python script for calculating NDVI and cropping the raster outside the TG boundaries

```python
import rasterio
from rasterio.mask import mask
import fiona
from pathlib import Path
import numpy as np

input_raster = Path(r'D:\GIS_DATA\raw_rasters\sentinel_2024.tif')
tg_boundary = Path(r'D:\GIS_DATA\vector\tg_boundary.gpkg')
output_ndvi = Path(r'D:\GIS_DATA\processed\sentinel_ndvi_clipped.tif')
```

```
# Channels: let's say 3 – Red, 4 – NIR (depends on the specific product)
RED_BAND = 3
NIR_BAND = 4


with fiona.open(tg_boundary, layer="boundary") as shp:
    geom = [feature['geometry'] for feature in shp]


with rasterio.open(input_raster) as src:
    # Cropping the raster along the TG boundary
    out_image, out_transform = mask(src, geom, crop=True)
    out_meta = src.meta.copy()
    # Calculating NDVI
    red = out_image[RED_BAND - 1].astype('float32')
    nir = out_image[NIR_BAND - 1].astype('float32')
    ndvi = (nir - red) / (nir + red + 1e-6)

    out_meta.update({
        'count': 1,
        'dtype': 'float32',
        'transform': out_transform
    })

    with rasterio.open(output_ndvi, 'w', **out_meta) as dst:
        dst.write(ndvi, 1)
```

Appendix C. SQL scripts for quality control of geospatial data in PostGIS

Appendix C.1. Example of an SQL script for checking the validity and correcting geometries in PostGIS

```sql
-- Search for invalid objects in the parcels layer
SELECT gid
FROM public.parcels
WHERE NOT ST_IsValid(geom);
```

```sql
-- Correct geometries using ST_MakeValid
UPDATE public.parcels
SET geom = ST_MakeValid(geom)
WHERE NOT ST_IsValid(geom);
```

```sql
-- Additional check for self-intersections
SELECT gid
FROM public.parcels
WHERE ST_IsSimple(geom) = FALSE;
```

Appendix C.2. Fragment of a Python script exported from ModelBuilder for batch conversion processing

```python
import arcpy
from arcpy import env
```

```python
env.workspace = r'D:\GIS_DATA\raw_gdb.gdb'
env.overwriteOutput = True
```

```python
target_gdb = r'D:\GIS_DATA\processed_gdb.gdb'

target_spatial_ref = arcpy.SpatialReference(5561)  # USK-2000, example


feature_classes = arcpy.ListFeatureClasses()


for fc in feature_classes:
    print(f'Processing layer: {fc}')
    proj_fc = arcpy.management.Project(
        in_dataset=fc,
        out_dataset=f'{target_gdb}\\{fc}_proj',
        out_coor_system=target_spatial_ref
    )


    repaired_fc = arcpy.management.RepairGeometry(
        in_features=proj_fc,
        delete_null="DELETE_NULL"
    )


    integrated_fc = arcpy.management.Integrate(
        in_features=repaired_fc,
        cluster_tolerance="0.01 Metres"
    )
```