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METHODS AND MEANS OF PROCESSING SATELLITE DATA FOR MONITORING ON THE EXAMPLE OF THE TERRITORY OF UZBEKISTAN

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Content

INTRODUCTION

In recent decades, scientific groups and organizations in various countries have been actively exploring the possibilities of satellite remote sensing for environmental monitoring. The advancement of remote sensing technologies has significantly expanded the possibilities of practical environmental monitoring. The data obtained helped to identify the consequences of fires, track deforestation, observe changes in natural ecosystems, control land use and solve other problems. Special attention was paid to the development of monitoring systems for agriculture and urban areas. In Uzbekistan, over the past 15-20 years, there have been significant changes in land use for economic reasons. The structure of land use has changed, and large tracts of land previously allocated for agricultural production now remain unused. Objective information is needed on changes in agricultural land use [3]. Currently, land use management is mainly carried out by the State Committee of the Republic of Uzbekistan for Land Resources, Geodesy, Cartography and State Cadaster through statistical observations. However, the information collected is of a general nature and is not subject to proper control over its reliability. As a result, the existing system for collecting land-use data does not fully comply with modern standards. Monitoring of changes in agricultural land use is becoming an integral part of the regulation system of the agro-industrial complex [6, 8].

In the field of agricultural monitoring, the Ministry of Agriculture and Water Resources of the Republic of Uzbekistan and the Agency for Space Research and Technology under the Council of Ministers of the Republic of Uzbekistan are working together to create their own satellite-based agricultural monitoring system, which is designed to obtain reliable information on the use of agricultural land. An important element of this system is the collection of data on the availability and use of arable land, including information on the geographical distribution of these lands and the crops used, as well as data on crops and operational monitoring of the condition of crops. The system is designed to provide users with information about the area of arable land, a variety of crops, their yields and the condition of crops. The use of remote sensing data plays a key role in assessing the use of agricultural land. Satellite imagery is an additional data source that needs to be monitored regularly. Among the important advantages of satellite images, their timeliness, objectivity and independence should be highlighted. Previously, the creation of operational monitoring systems was hampered by limited access to data from modern satellites, the lack of necessary software and hardware, as well as imperfect methods of thematic image processing. However, in recent years, the advent of new satellite systems has greatly simplified access to remote sensing data. It is important to note that without appropriate pre-processing and image processing algorithms, remote sensing information cannot be used effectively [8].

The development of remote sensing data processing methods for crop monitoring will contribute to improving the accuracy and objectivity of land-use information. This is an important stage in the creation of land-use maps based on remote sensing data. Taking into account the world experience and the level of development of modern satellite monitoring systems and computer technologies, the development of methods for automatic processing and analysis of satellite observation data seems promising. This technology plays an important role in the creation of a monitoring system for agricultural land in Uzbekistan [2].

Monitoring of agricultural land includes covering large areas and, consequently, processing a significant amount of remote sensing data. The main purpose of this study is to develop an algorithm that will automate this process of processing remote sensing data as efficiently as possible. The state and dynamics of land use are key aspects of modern ecology. Changes in the use of arable land can affect the microclimate and landscape, which in turn affects carbon dioxide emissions.

In recent years, almost all regions of Uzbekistan have faced the process of degradation of agricultural lands, which has led to soil erosion, a decrease in their fertility and the spread of shrubs. At the same time, crop failure is a natural phenomenon that complicates the management and control of agricultural land. For example, inefficient use of land, including ignoring the principles of crop rotation, can contribute to soil erosion, which ultimately leads to a long-term decrease in its fertility. Therefore, an objective approach to land use management is required both at the level of individual agricultural areas and at the state level [2].

Given the importance of agriculture for the environment, economy and social sphere in Uzbekistan, as well as the lack of objective, practical and reliable information about arable land, the development of a methodology for monitoring their condition using satellites is becoming extremely relevant and necessary. This determines the relevance of the presented research.

As it is known, current demographic forecasts and trends indicate that the world's population will continue to grow in the coming decades. At the same time, the demand for natural resources and living space will grow. As a result, urban areas are expanding significantly, and new settlements and urban agglomerations are emerging all over the world. Therefore, in order to solve problems related to current and future urbanization trends, data and methods are needed to observe and quantify the changes associated with urban expansion. The purpose of this work is to develop an analytical scheme to identify patterns of urban growth based on remote sensing data at various scales and spatial and temporal resolutions. This paper also attempts to assess the environmental consequences of urbanization using the concept of established landscape indicators, their extensions and combinations. It is worth noting that urbanization occurs unevenly, varying greatly in space and time. The unique and often chaotic growth of urban areas currently taking place is particularly noticeable in Central Asia. Uzbekistan has been experiencing rapid urbanization, especially since mid-2001. The demand for new residential, commercial and industrial land stimulates the emergence of new urban centers, which threatens sustainable development, the creation of a high quality of life and the protection of environmental sustainability [9].

Many scientists have proposed various methods to solve the above problems. However, the accuracy of these methods does not always meet the requirements, solves the problem only partially and requires significant computational costs. Therefore, the development of methods for processing, segmentation and detection of objects in urban and agricultural areas based on satellite data remains an urgent task.

The purpose of the study. The main purpose of the dissertation research was to develop automation methods, algorithms and tools, as well as appropriate software for processing data obtained from satellite observations in order to solve monitoring problems in agriculture and urban areas. The following approaches have been proposed to achieve this goal:

1. Development of an atmospheric correction algorithm for the formation of satellite data sets free from the influence of atmospheric distortion. This algorithm will improve the accuracy of segmentation of satellite images of the Earth and the reliability of the results obtained, as well as make it possible to unify images obtained from different satellites.
2. Development of a satellite data processing method for the identification of agricultural products in agricultural territories. This method will allow classification by types of products grown on agricultural land.
3. Development of a method for identifying urban objects by analyzing and segmenting satellite data. This method will make it possible to classify objects located in urban areas, and will also make it possible to identify newly built objects.
4. Development of satellite data processing software for solving agricultural problems and monitoring urbanization. This software will improve the quality of satellite data using atmospheric correction, provide data on the state of agricultural territories and types of agricultural products grown in these territories, and will also allow monitoring urban areas.

Scientific novelty. The following new scientific results were obtained in the work:

1. Based on deep learning approaches, a method for atmospheric correction of satellite images is proposed. The method allows for unified atmospheric correction for images obtained from different types of satellites.
2. Methods for assessing the state of agricultural zones and classifying crops using algorithms for determining vegetation indices and deep learning methods are proposed. The methods allow us to obtain objective information about the distribution and condition of agricultural land, cultivated crops, as well as about the distribution of urban land.

3. A method based on modification of the architecture of a deep learning neural network is also proposed, which allows segmenting and identifying objects on satellite images of territories, including urban and agricultural areas. The method allows to significantly reduce the requirements for computing resources needed to solve such problems.

Research methods. The work uses methods of digital image processing, machine learning methods, and methods of mathematical statistics.

Practical significance. The developed method of preprocessing remote sensing data makes it possible to obtain images free of clouds and other interfering factors. The resulting images are used to solve various remote sensing problems. The developed method of crop identification was used to obtain data on the spatial distribution of winter crops, sunflowers and clean fallow lands in the Ferghana region. The result of this study was the creation of an important software tool for the national monitoring system of agricultural lands and urban areas being developed in Uzbekistan.

Approbation. The main results of the dissertation work were reported and discussed at scientific seminars of the Department of Computer Modeling and Multiprocessor Systems of St. Petersburg State University, as well as at eight international scientific conferences:

Proceedings of the 9th International Conference "Distributed Computing and Grid Technologies in Science and Education" (GRID'2021), Dubna, Russia, July 5-9, 2021.

1. The 1st International Conference on Problems and Perspectives of Modern Science: Icppms-2021, Tashkent, Uzbekistan, 10–11 June 2021.
2. Modern Methods of Applied Mathematics, Control Theory and Computer Technologies (Pmtukt-2021), Voronezh, Russia, December 14–16, 2021.
3. Digital Region: Experience, Competencies, Projects Bryansk, Russia, November 26–27, 2020.
4. International Scientific Conference Proceedings “Advanced Information Technologies and Scientific Computing” PIT 2021, Samara, Russia.
5. International Scientific and Technical Conference "Advanced Information Technologies" (PIT-2022), Samara, Russia, April 18 - 21, 2022.

6. 10th International Conference "Distributed Computing and Grid Technologies in Science and Education" (GRID'2023), Dubna, Russia, July 3-7, 2023.

Publications. During the research, nine scientific papers were published, which contain the main results. All data processing methods, software and analysis of the results were developed and applied by the authors of the study independently. List of author's publications:

1. Grishkin V. et al. Detection of Fertile Soils Based on Satellite Imagery Processing [Electronic resource] / V Grishkin, E Zhivulin, A Khokhriakova, S Karimov // Ceur Workshop Proceedings. – 2021. – P. 251-255. - Access mode: https://doi.org/10.54546/mlit.2021.13.12.001 (date of access: 24.03.2024).
2. Grishkin V. M., Karimov S. I. Use of satellite imagery and index control to monitor and analyze the agricultural lands of Bukhara region, which is a world historical heritage [Electronic resource] / V Grishkin, S Karimov // AIP Conference Proceedings. – AIP Publishing, 2022. – Vol. 2432. – №. 1 - Access mode: https://doi.org/10.1063/5.0089537 (date of access: 25.03.2024).
3. Karimov S. I. Structural strategy for the formation of remote monitoring of agricultural lands // Modern methods of applied mathematics, control theory and computer technologies (PMTUKT-2021). – 2021. – P. 59-62.
4. Karimov S. I., Karimova M. I., Grishkin V. M. General description of the reception and study of data coming through the satellite // Digital region: experience, competencies, projects. – 2020. – P. 1044-1047.
5. Grishkin V. M., Karimov S. I. U. Models and methods of data processing remote sensing // The American journal of engineering and technology. – 2021. – Vol. 3. – No. 02. - P. 67-74.
6. Grishkin V. M. et al. Comparison of multi-resource remote sensing data for vegetation indices. – 2021.
7. Karimov S.I. Machine learning methods for predicting yield using sentinel-2 satellite images // International scientific and technical conference "Advanced Information Technologies" (PIT-2022). – 2022. – P. 163-169.

8. 124. Grishkin V.M., Karimov S.I. Deep neural network for semantic segmentation of satellite images // H&ES Reserch, 2024, Vol.16, No. 3, P. 12-17.
9. 125. Grishkin V. M., Karimov S. I. Atmospheric correction of satellite images using a neural network // Physics of Particles and Nuclei, 2024, Vol. 55, No. 3, P. 545–547.

Certificates of state registration of programs.

1. Certificate of state registration of a computer program No. RU2023664858 Russian Federation // Program for recognition and segmentation of objects on satellite images" (SatObj) // No. 2023663505: application. 06/28/2023: publ. 07/10/2023 Bulletin. No. 7 // V. M. Grishkin, S. I. Karimov // Federal State Budgetary Educational Institution of Higher Education "St. Petersburg State University" (SPBGU).

The structure and scope of the dissertation. The work consists of an introduction, four chapters, conclusion and bibliography. The total volume consists of 124 pages. Bibliography consists of 125 titles.

The main scientific results of the dissertation work:

1. An atmospheric correction method has been developed and implemented for processing satellite monitoring data on agricultural and urban lands. This method allows to obtain satellite images that are not affected by the properties of the atmosphere, and also makes it possible to unify images obtained from different satellites [1, 7, 125]. The operating principle of the new method is presented in [125] and in section 3.4. The author made 90% contribution to the development of atmospheric correction.
2. Methods of segmentation of satellite images for monitoring agricultural territories and classification of agricultural products grown in these territories have been developed and implemented [2, 3, 6, 124]. The process of segmenting agriculture by index VI and the process of analyzing index indicators are presented in article [2-3, 6] and sections 2.3 – 3.6. At this stage, the author’s contribution to obtaining the results was 95%. The process of identifying and segmenting types of agricultural products is reflected in sections 3.7 and [123-124] of the program and

article. The author made 85% contribution to the results of experiments and determination of the type of agricultural products using neural networks.

3. To study urban and rural areas, a method for processing satellite data using deep learning neural networks has been developed and implemented. Using this method, it is possible to identify certain objects in both urban and rural areas [1-7, 123, 124].

Using the developed methods, it was possible to improve the understanding of the distribution of urban lands in the Republic of Uzbekistan and control agricultural land, determine the quality of arable land, determine the types of crops grown on these lands [1, 2, 3, 123, 124, 125].

The main provisions submitted for protection.

1. Atmospheric correction method for processing satellite monitoring data of agricultural and urban lands. This method allows to obtain satellite images that are not affected by the properties of the atmosphere, and also makes it possible to unify images obtained from different satellites.
2. Methods of processing satellite images to assess the state of agricultural zones and classify crops using algorithms for determining vegetation indices and deep learning approaches.

The method of segmentation and identification of objects in satellite images of areas of interest, including urban and agricultural areas. The method is based on a modification of the architecture of a deep learning neural network and reduces computational costs when processing these images.

CHAPTER 1. ANALYSIS OF REQUIREMENTS FOR THE FUNCTIONAL STRUCTURE AND CHARACTERISTICS OF THE EARTH SATELLITE MONITORING SYSTEM IN UZBEKISTAN

1.1. Features of agricultural production and the main tasks of land monitoring

The development of productive agriculture is an important factor in economic progress in Uzbekistan. According to 2004 data, the population living in rural areas was 16.3 million people. About 8.7 million people are employed in agriculture annually, which is about 52% of the total employed population in the country. Agriculture is represented by approximately 12% of agricultural enterprises, 75% of households and "dean farms", which together produce 62% of all agricultural products. At the same time, 5.5 percent of Uzbekistan's GDP is produced in agriculture (2006). The agricultural sector is divided into two main branches: crop production and animal husbandry. Crop production accounts for 55.1% of total agricultural production (at current prices in 2004). The volume of production of main crops has remained stable in recent years, despite the constant reduction in acreage. Crop production is used both for export and for the domestic market.

Uzbekistan has 20 million hectares of agricultural land, including 3.2 million hectares of arable land, 10.5 million hectares of pastures, 3 million hectares of deposits and 2.8 million hectares of perennial plantations (as of 2004). However, not all arable land is actually used: In 2004, only 12.8 million hectares of arable land were used, which were distributed among the following crops: 31% - forage, 9% - industrial, 10% - winter, 41% - spring and 10% - vegetable. The net fallow areas amounted to 5 million hectares. The production of major crops is concentrated in several regions with the most favorable climatic conditions. They are located mainly in the southern regions, Surkhandarya region and Ferghana Valley. Crop production is very intensive in almost all regions of Uzbekistan. They account for more than 50 percent of the total sown area [8]. The 15 regions with the largest sown areas account for 73% of the total sown area of Uzbekistan

(2004). Most of the arable land is occupied by farmers, who account for 82 percent of the total cultivated area.

Figure 1.1 - The state of agricultural development in Uzbekistan in 2017-2020

Between 1996 and 2017, the area of arable land decreased by 8 million hectares (35 percent). Abandoned arable land is formally still agricultural land, but it is often no longer suitable for further use in agriculture. At the same time, the spatial heterogeneity of the process of abandoning agriculture and the inefficiency of traditional data collection systems on the state of the agro-industrial complex make it difficult to obtain the necessary management information in a timely manner.

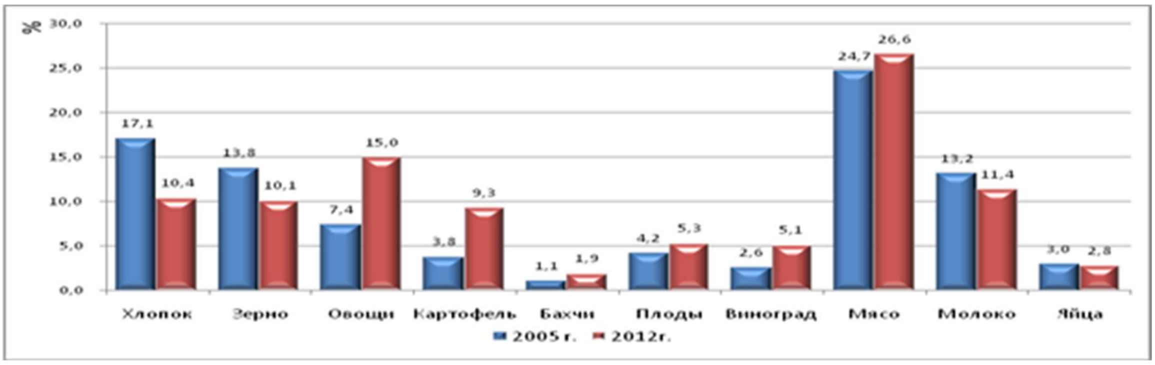


Figure 1.2 – Dynamics of the share of certain types of agricultural products in the total volume of agricultural production

The main reason for the reduction in the acreage of forage crops was a sharp decrease in livestock production. At the same time, the acreage of economically valuable crops decreased slightly, and the acreage of industrial and other crops increased. A comparison of the structure of crops from 2010 to 2017 is shown in Figure 1.3. changes in the structure of crops mainly affect the fertility of arable land. Wind erosion of the soil is a prerequisite for reducing soil fertility in areas with a light mechanical composition of the soil and strong winds.

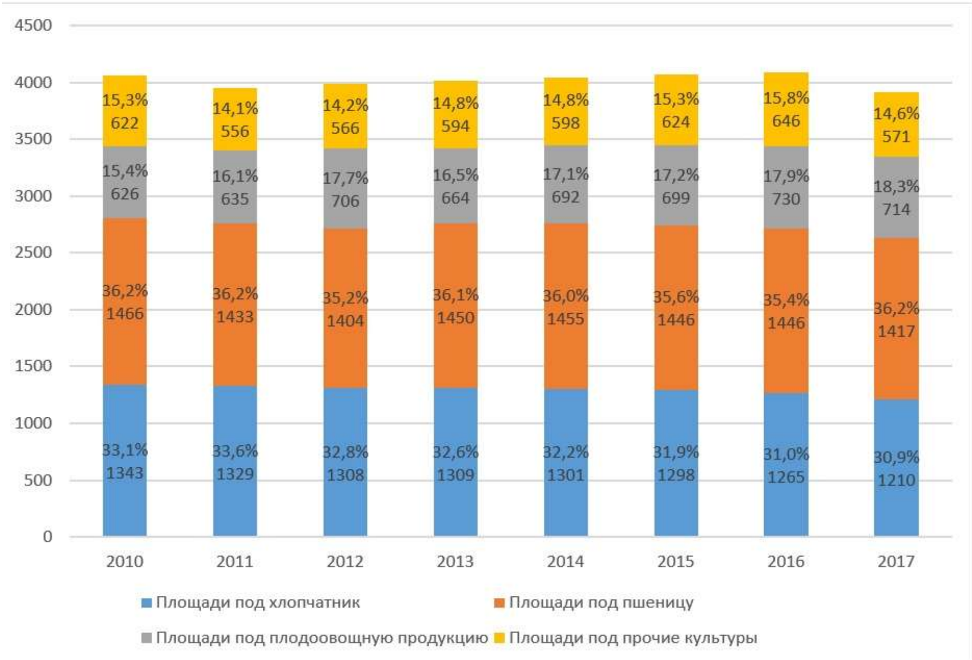


Figure 1.3. Distribution of agricultural land allocated for acreage, orchards and vineyards

Meanwhile, a decrease in the activity of arable land use had a beneficial effect on soil fertility in the steppe zone. Changes in the structure of crop rotation violate scientific principles related to soil cultivation and lead to significant degradation of humus, which negatively affects soil fertility.

Changes in the use of agricultural land in Uzbekistan and the growing need for effective and sustainable management of the agro-industrial complex at all levels emphasize the importance of objective and periodically updated information on the properties of agricultural land. Currently, the State Committee of the Republic of Uzbekistan is collecting such information. The features that complicate the objective management of the situation in agricultural production include a large number of small business entities (agro-enterprises) and the extremely disparate geographical location of business entities. The information provided by agricultural enterprises is partially processed by regional agronomists, but this is an extremely time-consuming task. Therefore, information on the area of crops of various crops and other aspects of agricultural production is provided by agricultural producers to the regional bodies of national statistics, but there is no system for verifying the reliability of this information. The statistical observation system does not provide data on the spatial distribution of crops, since agricultural producers report only the total area of available and used agricultural land, but do not specify which crops are grown on these lands. Thus, information on the placement of crops and actual land use is not regularly collected in traditional agricultural monitoring systems in Uzbekistan. In addition, the existing detailed land use maps of Uzbekistan contain only general summary data.

It is necessary to effectively monitor changes in land use. Information on the most important parameters of agricultural production is also needed for the organization of the agro-industrial complex. Systems for collecting such data should be characterized by objectivity, efficiency, correspondence in time and space in determining indicators, accuracy and a high degree of independence from agricultural producers.

Therefore, there is an urgent need for systematically updated and spatially coordinated information on the availability and actual use of arable land at the regional and national levels. This information should include data on the use of arable land and its changes over time, the area and condition of crops of various crops, as well as changes in the structure of crops. The existence of systems for collecting such information that meet modern standards contributes to improving the accuracy and reliability of forecasts of agricultural production parameters, as well as increasing the effectiveness of information support for decision-making in the agro-industrial complex, including support for agribusiness through subsidies. Given the growing concern about global climate change, accurate data on agricultural land dynamics and land use patterns play a key role in conducting basic research. By improving land use systems, optimal strategies can be developed to minimize carbon dioxide emissions into the atmosphere.

In order to obtain more complete and reliable information on the actual use of agricultural land in 2017, agricultural land was monitored in Uzbekistan. As part of the monitoring, no field studies were conducted to collect information on the spatial distribution of crops, but information was collected from large farming organizations. Due to the high cost of such continuous research, future research will be conducted with a five-year cycle. Thus, the annually updated information on the condition and spatial distribution of agricultural land will be a significant addition to the data collected during the agricultural census.

1.2. The capabilities of satellite remote sensing tools in solving the tasks of monitoring agricultural land

From the very beginning of space exploration, starting with the first conventional images taken by the American satellite ERTS-1 (later renamed Landsat) in 1972, and ending with satellite systems created by various countries to explore natural resources, remote Earth observation has become one of the most important tasks. The data obtained as a result of remote sensing from satellites are used for various purposes of Earth monitoring, including agricultural surveying. Remote sensing data in the visible, near infrared and mid-infrared ranges of the electromagnetic spectrum are most widely used for vegetation monitoring. Satellite images in these spectral ranges can effectively distinguish green vegetation from other types of vegetation cover. Studies conducted on the basis of data from ground and aerial observations [10,11,12] have studied in detail the reflective characteristics of agricultural crops. The main factors determining the reflective properties of vegetation are the presence of chlorophyll and other phytochromes, leaf structure and vegetation cover layout.

One of the main aspects of remote sensing data is the ability to provide high spatial resolution. Such data is usually classified into four main categories: low-resolution data (up to 1 km), medium-resolution data (150-300 m), high-resolution data (20-80 m) and extremely high-resolution data.

The AVHRR instrument provides images of the earth in six spectral channels with a resolution of 1.1 km in nadir. Due to the presence of several NOAA satellites in orbit, the survey cycle of any site takes only a few hours. Data acquisition is possible online via standard antennas, and archived data is provided free of charge by many government and scientific organizations. For example, archival survey data has been available since 1973 through the U.S. Geological Survey.

In recent years, satellite devices (Terra/Aqua-MODIS, Envisat-MERIS) have been increasingly used to obtain images of the Earth's surface with moderate spatial resolution (250-500 m). These devices are distinguished by the presence of numerous spectral channels and shooting in a narrow spectral range up to 10 nm wide. This makes it possible to observe the absorption bands of chlorophyll, water and other significant components, increases the accuracy of identification of subsurface objects and assessment of their condition by spectral characteristics. Devices with a wide bandwidth provide the ability to observe any point of the earth's surface for one to two days. In areas of intensive agriculture in Uzbekistan, where the size of agricultural land exceeds the spatial resolution of the data obtained by several orders of magnitude, it is necessary to have a sufficient number of frequent high-frequency observations. Therefore, MODIS offers data visualization in 36 spectral channels in the range from 0.4 to 14.4 microns. The spatial resolution of the infrared and near infrared data channels for vegetation monitoring is 250 meters. The Terra and Aqua satellites are part of NASA's experimental Earth Observation System (EOS) program.

By launching the Copernicus Earth monitoring program, the European Space Agency (ESA) has set itself an ambitious goal - to create a network of satellites that will collect a wide and diverse range of data on the state of the Earth. All these indicators will be processed and summarized to get a complete Figure of the changes taking place on Earth. Different groups of users will have access to the information they are interested in. Sentinel-1A, the first satellite of the Copernicus program, has been in orbit since April 2014. A fully operational constellation of two Sentinel-1 radar satellites will receive detailed radar images of the Earth's surface and compare them with optical images obtained by Sentinel-2. As a result, the most complete and accurate image of the Earth's surface will be obtained.

Sentinel-2A and 2B are projects from the European Space Agency (ESA) Sentinel, which are equipped with multispectral optoelectronic sensors capable of receiving images in the visible, near infrared and shortwave infrared ranges with a resolution of 10 to 60 meters. They include 13 spectral channels and 3 spectral channels and are able to detect differences in the state of vegetation, including temporary changes, minimizing the impact of atmospheric conditions on image quality. The average altitude of the orbit is 785 km and two satellites in flight allow images to be repeated every five days in the equatorial regions and every two to three days in the middle latitudes. In addition to the high repeatability of images, the increased capture width allows to track rapidly changing processes, for example, changes in the structure of vegetation during the growing season. The Sentinel-2 mission is unique in its combination of covering large areas, frequent repeat surveys and systematically obtaining high-resolution multispectral images with full coverage of the entire Earth. For free viewing, analysis and downloading of images received from Sentinel-1, 2 and 3 satellites with low and medium resolution, use the online portals EO Browser and Sentinel Playground. Sentinel Playground is an interactive portal that allows to view and analyze mosaics of images obtained using Sentinel and Landsat satellites.

High-resolution images of the Earth's surface are provided by a number of satellite systems. The most widely used satellites are the MSS (Landsat-1, 2, 3, 4 and 5), TM (Landsat-4 and 5) and ETM+ (Landsat-7) Landsat series. The most modern ETM+

instruments have eight spectral channels covering the range from 0.4 to 13 microns, with a resolution from 15 to 60 meters. Data from ETM+ is available commercially, but the University of Maryland provides free access to an extensive global archive of images.

The use of remote sensing data for monitoring agricultural lands began back in the 1970s. The purpose of monitoring determines the type of equipment used to receive data. Low-resolution satellite instruments are used for global monitoring, which allow obtaining data on the entire surface in a short period of time, but do not allow collecting information about individual agricultural fields. The medium resolution data has a high frequency of observations and spatial resolution, which is sufficient for monitoring large rural areas.

In order to effectively solve thematic problems in agricultural monitoring, pre-processing of spatial images is often required. This is especially important for detecting pixels obscured by clouds or covered with snow, as well as for identifying pixels that have been disrupted due to hardware failures. Previously, the selection of cloudless and clean images was carried out manually by operators, however, with the increase in the volume of remote sensing data, there was a need for automated methods and preprocessing systems [12]. Pretreatment consists of atmospheric corrections that occur when radiation reflected from the Earth's surface passes through the atmosphere.

Due to the high dimensionality of the analyzed data space (multispectral images of different time periods), a full-fledged tracking system becomes impossible without creating a complex of algorithms for primary image processing and object interpretation [11]. The main tasks here are to select the most appropriate classification characteristics and reduce the dimension of the analysis space. Vegetation indices (VI) can be used as an intermediate step in reducing the dimension in assessing the volume and condition of green vegetation, the applicability of a particular index depends on the characteristics of the task to be solved. For example, the source [15] analyzes the comparison of values of vegetation indices using different data sets, while articles [11, 16] compare the applicability of EVI and NDVI indices calculated on the basis of these data with pure vegetation indices. The article [16] also describes the possibility of determining EVI based on the values of vegetation indices. It should be noted that in order to ensure comparability of the values of vegetation indices calculated from data from various instruments, special calibration of the satellite data obtained is required.

Many studies based on high-resolution data are focused on analyzing the applicability of remote sensing in limited areas. These data can be used to compile maps and assess the condition of major crops, ranging from individual farms to several administrative districts [17]. The use of remote sensing has also proved useful for assessing the impact of floods on crops [19]. Research based on high-resolution data is an important tool for studying various aspects of remote sensing applications in precision agriculture.

The potential of using high-resolution data is being actively studied among some farmers within the framework of the concept of "precision farming" [18,19]. The use of remote sensing helps farmers to improve the efficiency of fertilizer use, monitor the condition of crops and assess the impact of negative factors on yields. Information obtained using high-resolution data can be an important tool for optimizing agricultural methods [20].

Low-resolution information can provide a rough idea of crop growth. In such situations, image classification is usually used, covering a relatively small number of objects [21]. These data can be used to assess yields and determine the timing of plant phenology [22].

In the study [23], high-resolution data (for example, MSU-E, HRV-SPOT), medium-resolution data (for example, MSU-SK) and low-resolution data (for example, NOAA-AVHRR) were used to map the soil and vegetation cover of agricultural territories. The results of thematic processing of high-resolution images provide material for educational analysis of medium-resolution images, which can be extended to a wider range. The researchers conclude that the use of medium-resolution data (Terra-MODIS) is promising. High-resolution (e.g. Landsat) and medium-resolution data are also considered in the literature [24, 25]. Maps of vegetation diversity were developed on the basis of high-resolution data, while data from the MODIS tool were used to monitor leaf area indices and assess the yield of various crops.

The availability of medium-resolution data improves the accuracy of global monitoring compared to low-resolution data in remote sensing. These data make it possible to observe phenology in individual fields in a spatial and temporal context. Currently, research is actively underway on monitoring crops using medium-resolution devices [26,27], and data from Terra-MODIS are used to estimate the area of rice crops at both the national and subcontinental levels. The use of automatic classification methods has made it possible to obtain information on the spatial distribution of rice crops in several countries of Southeast Asia and China. Estimates of the area of crops were carried out, the results of which are in good agreement with official statistics. It should be noted that the study covered a vast area extending over 2.6 million square kilometers. The methodology used to map rice crops is based on a priori information and analysis of crop dynamics. The results of the study were compared with official statistics and the results of the classification of high-resolution images. Medium-resolution remote sensing equipment is capable of receiving data for the same area within one to two days. Attempts have been made to predict the phenology of rice using satellite data [28]. For example, using MODIS data, the date of rice sowing, the date of the beginning of flowering, the date of harvest and the duration of the growing season were predicted [29].

For grain crops, the relationship between the satellite-observed vegetation indices and yield has been established [30,31]. Due to the high frequency of observations of medium-resolution remote sensing, it is also possible to estimate the actual timing of sowing crops [32]. However, the accuracy of the simulation depends on the quality of the initial data on the biophysical parameters of the culture. Remote sensing is one of the sources of such data for modeling [33,34,35].

1.3. Urbanization and urban expansion

Urbanization is defined simply as "the movement of people from rural to urban areas, in which population growth corresponds to urban migration" (United Nations, 2005). Urbanization is also a social process that involves changes in behavior and social relationships as a result of people living in urban areas [36]. In fact, it includes a comprehensive lifestyle change resulting from the impact of cities on society [37]. However, nowadays urbanization is usually used in a broader sense and implies much more than just urban population growth; it includes the physical growth of urban areas, as well as changes in the socio-economic and political structure of the region as a result of population immigration to urban areas [38,39]. Urbanization is a dynamic and complex phenomenon taking place all over the world. This process, without signs of slowing down, led to significant changes in the land cover and landscape structure [39,40]. Rapid urbanization, especially in developing countries, will continue to be one of the important problems of global changes affecting the human dimension [39]. Due to the process of rapid urbanization, the spatial expansion of built-up areas is accelerating. Although urbanization contributes to socio-economic development and improves the quality of life, urban growth inevitably leads to significant changes in land cover in urban areas, for example, the transformation of forests and wetlands into agricultural or built-up land, as more land is used for production. goods and services, and for people living in cities, more residential land is needed. Although urban areas currently cover only 3% of the Earth's land surface [41], the transformations resulting from urban growth are among the most significant types of anthropogenic dynamics of land cover, and the environmental consequences of urban growth go far beyond urban boundaries [42,43]. This is especially relevant in rapidly developing regions, where vegetation changes caused by rapid urban growth have led to serious problems threatening sustainable urban development, for example, local and regional climate change, changes in the hydrological circle [44].

The process of urban growth can be characterized either as a change in the urban area (a measure of scale), or as the rate at which suburban land is transferred to urban use (a measure of speed) [45]. However, the scale and pace of urban growth cannot provide detailed information about spatial models of urbanization or the underlying processes. Therefore, the urban spatial structure has become another subject of interest for geographers and economists when studying changes in cities.

In the context of urban growth trends, much attention is paid to urban sprawl. In the late 1950s, the phenomenon of urban sprawl in the United States began to be widely studied. This is seen as a phenomenon accompanied by the expansion of urban areas with low population density. Later, similar processes of urban sprawl were described in most cities, including cities in developing countries.

Due to its diversity and complexity, many definitions of sprawl have been proposed. For example, the authors [46] suggested that urban sprawl occurs when land is consumed at a faster rate than population growth. [47] defined urban sprawl as a type of low-density development with separated residential, commercial and industrial areas, a lack of thriving centers of activity and a limited choice of travel routes. Similarly, [48] noted that urban sprawl has its own special spatial patterns: unlimited external and abrupt expansion of new buildings with low population density. Although there is no generally accepted definition of urban sprawl, there is a general consensus regarding the depiction of urban sprawl as a special type of urban expansion characterized by low density, dispersed spatial structure with environmental and social consequences [49,50].

1.4. Requirements for the functional configuration and characteristics of satellite monitoring systems for agricultural lands

In accordance with the Decree on the establishment of the National Space Agency of Uzbekistan, adopted in 2019, the formation of a national satellite monitoring system for agricultural land has begun in the country. The main purpose of the system is to provide reliable information on the use of agricultural land, including arable land. The satellite monitoring system will provide the Ministry of Agriculture and other public and private organizations with objective data on agricultural production. During the development of the monitoring system project, the following main objectives were identified:

1. Drawing up a basic map of indicators of agricultural land use during the period from 2017 to 2022;
2. Assessment of updating data and dynamics of arable land use - at the end of each planting season;

3. Determination of the area of fallow lands - at the end of each agricultural period;
4. Assessment of the use of fallow lands - annually for 6 weeks after the end of the agricultural season;
5. Assessment of the use of arable land for perennial crops - at the end of each agricultural season;
6. Assessment of compliance with crop rotation rules - updated annually at the end of the growing season;
7. The estimated area under cultivation for the current year is determined annually within 6 weeks from the beginning of the agricultural season and at its end;
8. Assessment of the area of winter crops - is carried out annually in autumn, after the end of the agricultural season;
9. Assessment of the safety of winter crops - annually, within four weeks after the start of the agricultural season;
10. Monitoring of crop growth during the intensive agricultural season;
11. The projected yield and total production of the main crops.

Maps of cultivated fields in Uzbekistan should become a fundamental information base for agriculture. The creation of such maps is a starting point for the development of further monitoring of crops. The use of crop detection algorithms will allow for an operational analysis of the situation in agriculture in the future. Therefore, the primary task of monitoring is to develop methods for mapping the spatial distribution of arable land and existing crops.

When developing requirements for monitoring systems of cultivated fields, the peculiarities of agriculture were taken into account. Monitoring of cultivated lands can be performed using various remote sensing devices with different characteristics, such as spatial resolution, spectral channels, refresh rate, and others. However, special conditions are required for effective remote sensing. When monitoring vegetation, for example, satellite images should be recorded in the spectral ranges that most accurately separate green vegetation from other species. The spatial resolution of the satellites used should be sufficient to observe individual agricultural fields. Crops are growing rapidly, requiring constant monitoring. An important factor in choosing satellite data was their price. Given that the monitoring system covers all agricultural areas of Uzbekistan, the cost of remote sensing makes the entire system expensive. Therefore, one of the key principles in the development of the monitoring system was the maximum use of free remote sensing data.

The data received from the instruments installed on the Terra and Aqua satellites perfectly meet these requirements. The surveillance systems have spectral channels covering the infrared and near infrared regions, and their spatial resolution is 250 meters. The wide viewing angle of the cameras allows to take figures of the territory of Uzbekistan at least once a day; in addition, Landsat-TM/ETM+ images were selected as an additional data source with high spatial resolution.

Due to the large area and wide spatial distribution of cultivated lands, the simultaneous use of several methods of visual interpretation of spatial images is almost impossible. The large volume of transmitted remote sensing data requires maximum automation of information processing in order to minimize the involvement of specialists. However, due to the presence of clouds and other factors, the effective use of remote sensing data for thematic analysis is impossible without pre-processing. Satellite data preprocessing algorithms should exclude surface areas unsuitable for thematic analysis, for example, cloud areas. Pre-processing should ensure that cloudless images are obtained for the entire monitoring area.

Thematic map processing algorithms should be able to create the necessary thematic maps, for example, crop distribution maps. Experts can easily identify different thematic categories using visual analysis, but it is very difficult to develop automatic algorithms for this purpose. However, without the use of automated algorithms, it is almost impossible to perform a thematic analysis of agricultural land data in Uzbekistan. These algorithms also guarantee the objectivity of the results, significantly reduce information processing time and reduce the need for human resources compared to traditional visual analysis. Based on the above-mentioned requirements, the configuration of the agricultural land monitoring system is determined as follows:

1. The subsystems responsible for collecting satellite data are aimed at obtaining, archiving and cataloguing the necessary remote sensing data. Given the vast amounts of remote sensing data, these processes require automation. The data from the following satellite systems turned out to be the most suitable for monitoring agricultural land:
    - Medium spatial resolution information obtained through the Sentinel satellite system covers the entire globe in one to two days. The images are formed in the visible and infrared regions of the spectrum. These data are ideal for operational monitoring of vegetation development.
    - The data from Sentinel-2 has a high spatial resolution. Contrary to this, they do not cover agricultural land with the required regularity, however, they can be used as additional data to the existing archive of historical photographs.
2. The role of the preprocessing subsystem is to prepare the data before the subject processing. Atmospheric correction algorithms are a necessary component of this subsystem. Such software should read data in standard formats, create composite data and provide a record of the results in the most convenient format for further processing.
3. An important element of this module is the object processing algorithm for remote sensing data. This set of algorithms should be able to objectively and reliably determine the selected categories of objects with minimal intervention from a specialist. In addition, the algorithms must demonstrate reliable results for vast territories with various climatic, relief and other geographical features. It is also important to develop specialized software to implement these algorithms.
4. The data distribution device should allow the user to select the necessary remote sensing data through an easy-to-use interface and access them in the shortest possible time. Distribution systems should ensure the provision of aggregated images obtained after the preprocessing stage, thematic maps and data reflecting the state of monitoring facilities. Information on monitoring results should be archived, systematized and provided with quick access. The most effective method

of distributing information is to provide a database over the Internet with a graphical user interface on a website for the convenience of users. At the same time, specialists using GIS software should be able to upload data in a specialized format.

Conclusion to the chapter 1

Monitoring the use of agricultural and urban land is a key factor for effective management of the main sectors of the economy. To achieve this task, it is necessary to have objective and up-to-date information on land use. Currently, Uzbekistan is actively developing a national monitoring system for agricultural and urban lands, which uses data obtained by remote sensing. The main objectives of this system include the creation of maps of arable land, maps of annual crops, maps for tracking the condition of crops, maps for assessing yields, maps for monitoring the use of urban land and maps for planning the placement of facilities. To achieve these goals, the most suitable are medium spatial resolution data, which have sufficient detail for operational monitoring over large areas, as well as high-resolution remote sensing data, which are used for research at the regional level. Currently available remote sensing data meets the requirements of vegetation monitoring in terms of speed, availability, cost and spectral availability. However, the use of remote sensing data to monitor large areas of agricultural land in Uzbekistan requires the development of systems for collecting, processing and distributing results.

The processing system should contain a module of automatic algorithms for preliminary and thematic data processing, which will allow manual processing of agricultural monitoring information without the involvement of specialists. The creation of automated algorithms for preprocessing remote sensing data will ensure their effective use for monitoring crops, urbanization processes and other satellite monitoring programs. It is necessary to develop thematic processing algorithms for determining the use of arable land, mapping crop types and monitoring the condition of crops.

CHAPTER 2. STUDY OF METHODS FOR CLASSIFYING EARTH REMOTE SENSING DATA

In recent studies [51], where remote sensing data from urban areas were used to analyze changes in the landscape, it is noted that combining these data with spatial indicators can provide more detailed and spatially consistent information about the structure and changes of urban areas than using each method separately. Also, in [52], the importance of developing indicators of the state of ecosystems based on GIS and remote sensing data for mitigation and planning is emphasized. Together, these tools can significantly improve our understanding of landscape change and use, which can have an impact on urban planning by improving its quality. The following sections present the history of the problem and recent advances in research related to the classification of remote sensing data in urban areas and the use of indicators to monitor landscapes and assess their environmental impact, including landscape parameters. To obtain significant indicators and metrics, it is necessary to carefully draw up land-use maps classified based on remote sensing data.

2.1.Application of medium and high-resolution multispectral data from the field of remote sensing

The information obtained from remote sensing data is an important source for the analysis of various territories. These data are characterized by high spatial consistency and detailed geometric information, and can also be obtained with high frequency over vast territories [51]. After classifying remote sensing data, it is possible to extract thematic information such as changes in the Earth's surface or land use. Classification of multispectral remote sensing data based on statistical pattern recognition methods is one of the most widely used methods for information extraction [53].

Parametric and nonparametric algorithms based on statistical methods, methods that do not require parametric assumptions, non-metric approaches, methods that do not use distance metrics, logical approaches to classification with observable and unobservable data, classification methods with hard or fuzzy boundaries between classes, classification algorithms focused on pixels or objects, object-oriented methods classifications, Hybrid approaches and other classification methods are used to create maps of vegetation cover and land use based on remote sensing data [54]. All classification methods involve a compromise between three aspects: the amount of spectral information in the image, the method used to determine the classification, and the class of information. The choice of classification method depends on the physical characteristics of the studied area, prior knowledge, distribution of remote sensing data and the specifics of the classification task.

This study focuses on the regional level for a comprehensive consideration of the urban area and its natural environment. This is also a key aspect for assessing environmental impacts, as the negative effects of fragmentation on biodiversity and ecosystem services are often observed at intermediate (regional) spatial scales. Many studies have been conducted at the level of regional territories, urban agglomerations and microdistricts [56,57,58,59,60], as well as at the global, continental and national levels [61,62,63,64,65,66]. However, there is still insufficient research linking urbanization to specific local environmental impacts, especially at the level of megacities. More research is needed, taking into account the landscape perspective [57,64].

Low-resolution, high-bandwidth data such as MODIS and AVHRR are suitable for continental and global studies, while VHR data such as Quickbird and Ikonos are suitable for more detailed, small-scale studies, such as suburban areas and specific types of habitats. Small-scale studies, for example, suburban areas and specific types of habitats. Medium and high-resolution satellite data are used for intermediate regional approaches because they provide the best compromise between spatial coverage and level of detail.

Before subjecting satellite data to thematic processing, they must be pre-processed in order to obtain realistic information about surface features. This is due to the fact that the reflected radiation recorded by satellites is distorted when passing through the atmosphere. Therefore, the first operation is to eliminate this distortion, known as atmospheric correction.

2.2.Methods and algorithms of atmospheric correction

Atmospheric correction in satellite image processing is the process of removing atmospheric effects from measurements taken with satellite imagery. The purpose of atmospheric correction is to eliminate atmospheric effects such as light scattering and radiation absorption, and to obtain more accurate values of the radiation properties of the Earth's surface. The atmospheric correction process consists of several stages [68]:

1. **Radiation measurement.** Obtaining measurements recording radiation from objects on Earth. These measurements may include brightness values in different channels of the spectrum, depending on the sensor used.
2. **Assessment of atmospheric parameters.** Assessment of atmospheric parameters such as optical thickness, transmission and other characteristics. These parameters can be estimated using atmospheric models, statistical methods, or other techniques.
3. **Correction of measurements.** Applying correction to measurements based on estimated atmospheric parameters. This may include subtracting the influence of the atmosphere or other mathematical operations to restore the true radiometric characteristics of the surface.
4. **Restoration of the surface reflectance.** Conversion of corrected measurements into reflectance, which is a fraction of the radiation reflected by the surface. The reflectance is a more stable and comparable value than the measured brightness values.

Atmospheric correction is important for accurate analysis and interpretation of satellite data. It allows to get more reliable and comparable results when comparing data from different time and spatial regions. There are several methods and algorithms of atmospheric correction for processing space images [69]:

1. **Dark Object Subtraction (DOS):** He is often associated with Jason R. Smith, who first proposed the concept of DOS in 1990. $R_{cor} = R_{raw} - D$, where R_{cor} is the corrected reflection, R_{raw} is the measured reflection, D is the correction.

The basic idea of DOS is to take into account the influence of dark objects (for example, shadows) on the image and adjust the pixel values to improve the accuracy of the data. How the DOS process works:

- Definition of dark objects: DOS begins by identifying objects in the image that can be considered "dark". This often includes shadows, dark clouds, water surfaces, and other objects that can contribute dark artifacts to the image.
- Dark Object Assessment: DOS evaluates the intensity of dark objects in the image. This may include calculating statistical parameters such as the mean or median of dark objects.
- Subtraction of dark objects: The estimated intensity values of dark objects are then subtracted from the original pixel values in the image. This allows to adjust the measured values, compensating for the influence of dark objects.
- Calibration and correction: Additional calibration and correction may be required to take into account the characteristics of the atmosphere, light and other factors affecting the image.
- The advantages of DOS include improved contrast and image quality, as well as more accurate extraction of information from pixels. This method is often used in the context of processing data from Earth observation satellites, such as data from Landsat and Sentinel, where atmospheric effects can significantly affect image quality.

2. **Flat Field Correction:** Also known as Flat Fielding, it is an image correction technique that is used in the field of optical and digital image processing. This method is used to compensate for uneven lighting or sensitivity of the image sensor over its entire surface. How Flat Field Correction works:

- Getting a Flat Field (Flat Frame): First needs to get an image called a Flat Field or Flat Frame. This image is usually an image obtained under uniform and intense lighting, in which there are no objects on the scene. Thus, any irregularities in lighting or sensor sensitivity, as well as any artifacts associated with the optical system, can be fixed.

- Flat Field Calculation: Flat Field is calculated by averaging several such images. It is important that the objects in the scene do not create shadows or changes in intensity in the image.
- Applying Correction: Flat Field is then applied to the actual images of the scene. Each pixel in the scene image is divided by the corresponding pixel in the Flat Field. This allows to compensate for any changes in the brightness or sensitivity of the sensor recorded in the Flat Field.
- Additional Processing: After applying Flat Field Correction, additional processing may be required, such as color correction, contrast alignment, and other steps, depending on the specific requirements of the task.

The use of Flat Field Correction is especially important in cases where the image quality is affected by uneven lighting or other artifacts that may occur during the photographing process.

3. **Empirical Line Method (ELM):** John Robert Rocks (John Robert Schott) is often associated with the development of the ELM method. It is a method used in image processing in remote sensing to correct and calibrate data. This method is usually used to improve the accuracy and calibration of satellite data, such as Landsat, Sentinel and others, by correcting atmospheric effects and other distortions. Linear regression is used to correct atmospheric effects.

$$R_{cor} = m * R_{raw} + b$$

where R_{cor} is the corrected reflection, R_{raw} is the measured reflection, m and b are the parameters of the linear regression. The algorithm of the method is as follows:

- Training data collection: First, training data is collected for the area that want to explore. This data includes survey measurements taken from sensors such as on-site spectrometers.

- Measuring the brightness of objects: The brightness (reflectivity) of various objects on the ground in various spectral channels is measured. Usually, several channels are used to account for different characteristics of the Earth's surface.
- Building an empirical line: Based on measurements, an empirical line is built that connects the brightness in the shooting image with the measured brightness on the ground. Linear regression is usually used to construct this line.
- Satellite data calibration: The empirical line is then applied to the data received from the satellite. This allows to adjust the brightness values on satellite images, taking into account atmospheric effects, shooting angles and other distortions.
- Verification and correction: The accuracy is checked and, if necessary, the empirical line is corrected. This process can be repeated to ensure the best accuracy.

The Empirical Line method is widely used in the field of remote sensing data processing and provides a powerful tool for correcting atmospheric effects and calibrating data.

4. **Radiative Transfer Models (RTM):** Radiation Transfer Models (RTM) are mathematical models that describe the interaction of electromagnetic radiation with the atmosphere, the Earth's surface and other objects. They are widely used in the field of remote sensing for the analysis and interpretation of data obtained from spacecraft and aerial photography. How RTM works:
   - Atmospheric radiation: RTM takes into account the interaction of solar radiation with various layers of the atmosphere. This includes the scattering, absorption and reflection of radiation by various atmospheric components such as molecules, aerosols and clouds.
   - Radiation from the Earth's surface: RTM simulates the interaction of solar radiation with the Earth's surface. This includes reflection, absorption and emission of thermal radiation, which depends on the properties of the surface.

- Transmission of radiation through the atmosphere: RTM takes into account how radiation reflected from the Earth passes through the atmosphere and reaches the sensor on a spacecraft or airplane.
- Detector measurements: The model predicts which measurements should be taken at the detector as a result of the interaction of solar radiation with the atmosphere and the Earth's surface.
- The main difficulty of RTM is to take into account the various physical processes occurring in the atmosphere and their interrelationships.

5. **MAJA (Multi-sensor Atmospheric Correction and Cloud Screening):** The MAJA method is developed and maintained by the French Space Agency (CNES) and is used in the context of many Earth observation missions such as Sentinel-2. The MAJA method is implemented in the appropriate software for atmospheric correction and cloud allocation in data received from various Earth observation sensors on satellites. The main features of MAJA:
   - Atmospheric correction: One of the main functions of MAJA is atmospheric correction. This includes modeling the interaction of sunlight with the atmosphere and the Earth's surface. MAJA takes into account aerosols, humidity, ozone and other atmospheric constituents to adjust brightness measurements according to the physical processes taking place in the atmosphere.
   - Cloud Highlighting: MAJA provides cloud screening by identifying cloud pixels in an image. This is important in order to exclude cloud areas from the analysis and ensure clean data of the Earth's surface. MAJA uses various methods, including cloud mapping, statistical methods, and others.
   - Multi-sensor processing: MAJA is designed to work with data from various sensors, including Sentinel-2, Landsat and others. This ensures the versatility and applicability of the program to various missions.

- Integration with other tools: MAJA can integrate with other data processing tools and platforms, which allows it to be used as part of larger data processing and analysis systems.

MAJA provides stable and reliable atmospheric correction and cloud processing for satellite Earth observation data, which makes them more suitable for various applications such as cartography, agriculture, ecology and many others.

6. **Py6S:** The 6S model was developed to simulate the effects of the atmosphere on radiation detected by sensors on spacecraft. The model takes into account the influence of the atmosphere on measurements obtained from Earth observation devices on satellites. Py6S is implemented as a library in Python, which is designed to work with the 6S model (Second Simulation of the Satellite Signal in the Solar Spectrum). Py6S provides a software interface for interacting with the 6S model, simplifying the process of simulating atmospheric effects on radiation in the observed spectrum. It can be useful for remote sensing research, atmospheric correction of satellite data, and other tasks.

Each method has its advantages and limitations, and the choice depends on the specific requirements of the task and the characteristics of the data. Some methods require knowledge of atmospheric parameters such as optical thickness, humidity, etc., while others may be less demanding on external data, but less accurate.

Among the existing software tools that implement, including atmospheric correction, Sen2Core software should be noted. Sen2Core is a software tool designed to process data from Sentinel-2 satellites belonging to the European Space Agency (ESA). It is part of the extensive Copernicus system, providing free access to Sentinel data and other space data for the public and scientific research. Sen2Core provides tools for processing Sentinel-2 data, including the following functions:

1. Correction of radiation errors: Sen2Core includes processes for correcting atmospheric effects such as aerosols and water vapor, which allows for more accurate measurements of radiation.

2. Geometric Correction: The tool provides geometric correction tools, including improved image registration and elimination of geometric distortions.
3. Processing of various products: Sen2Core is capable of processing various products, including the high-resolution level (Level-1C) and the top-level level (Level-2A).
4. Integration with data processing tools: Sen2Core can be used in various data processing environments, including graphical user interface (GUI) and command line.

As a rule, one or another atmospheric correction method is implemented as part of the software of the corresponding data processing centers for each satellite family. These processing centers provide users with satellite images with various levels of processing, including images for which atmospheric correction has been performed. However, atmospheric correction is not carried out for all data received from satellites. For example, for Sentinel-2 satellites, atmospheric correction is missing for a large number of images taken earlier than 2018. At the same time, users can independently pre-process the data they are interested in, including atmospheric correction, using appropriate application programs. However, this processing is carried out interactively for each image of a specific area, which does not allow for automatic processing of sufficiently large sets of such images. Therefore, this paper proposes a method that allows to automate the process of atmospheric correction of "raw" satellite images using a simple convolutional neural network implementing the encoder - decoder architecture. Images without atmospheric correction are received at the input of this network, and the result of its operation will be images with atmospheric correction. The network is trained on a dataset formed from images of the earth's surface with atmospheric correction already performed and images of the same areas without it. The proposed method is discussed further in the third chapter of the work.

2.3. Spectral indices

Spectral indices are numerical characteristics obtained from data on the spectral reflectivity of various wavelength ranges of the electromagnetic spectrum. These indices are used in various fields such as agriculture, ecology, and geology to estimate various parameters of the observed territories using satellite or aerospace data. In addition, they can be used for preliminary segmentation of the obtained images by types of the earth's surface. These indices are usually calculated using values from various spectral regions such as visible light, infrared and ultraviolet regions. The values of conditional symbols used in formulas are given below [1]:

• NIR - pixel values from the near infrared channel.

• RED - reflection in the red region of the spectrum.

• SWIR – pixel values from the shortwave infrared channel.

• L is the value of the green vegetation cover. It is often used in desert areas where vegetation cover is negligible and results range from -1.0 to 1.0.

• BLUE – pixel values from the blue channel.

• GREEN - pixel values from the green channel.

When processing spectral data obtained during remote sensing of the Earth, the following spectral indices are most often used:

1. **NDVI (Normalized Difference Vegetation Index):** Assessment of vegetation health. Green plants strongly absorb light in the Red and near infrared (IR) ranges, which makes NDVI useful for monitoring plant growth.

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

2. **EVI (Enhanced Vegetation Index):** An analogue of NDVI, but with correction for atmospheric conditions and the influence of the soil background.

$$2.5 \times \frac{(NIR - RED)}{(NIR + 6 \times RED - 7.5 \times BLUE + 1)} \tag{2}$$

3. **NDWI (Normalized Difference Water Index):** Definition of bodies of water, such as lakes and rivers. Water strongly absorbs in the near infrared (NIR), while vegetation usually reflects.

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR} \quad (3)$$

4. **NDSI (Normalized Difference Snow Index):** Snow and ice detection. Snow reflects strongly in the green and shortwave infrared (SWIR) bands.

$$NDSI = \frac{GREEN - SWIR}{GREEN + SWIR} \quad (4)$$

5. **SAVI (Soil-Adjusted Vegetation Index):** Correction for the soil background, which makes it more sensitive to changes in vegetation density.

$$SAVI = \frac{NIR - RED}{(NIR + RED + L) \times (1 + L)} \quad (5)$$

where L is a constant (usually 0.5).

6. **MSAVI (Modified Soil-Adjusted Vegetation Index):** Correction for the soil background, taking into account a higher sensitivity to green vegetation.

$$MSAVI = 0.5 \times (2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - RED)}) \quad (6)$$

Spectral indices are widely used in various fields, including agriculture (for crop monitoring), ecology (for tracking changes in vegetation cover), geology and remote sensing. The calculation of these indices helps to highlight features of objects that may be difficult to identify with simple visual analysis of images. Spectral indices, including NDVI and SAVI, were used in studies aimed at analyzing agricultural land in order to identify and monitor agricultural land in Uzbekistan. In addition, the SAVI, NDVI and EVI indices were used to determine and pre-evaluate the level of fertility and productivity of agricultural land. The NDSI index can be used to determine the presence of snow cover in mountainous areas. These indices can also be used to evaluate irrigation efficiency, determine the optimal harvest time, and solve other agricultural tasks. Their use in combination with modern remote sensing data and satellite images allows for more accurate and efficient management of agricultural land. Thus, vegetation indices can be used as informative signs for a system for recognizing types of crops and the degree of their development [2].

2.4. Object analysis and image classification

Object analysis and image classification are image processing and data analysis techniques that focus on highlighting and identifying objects (objects can be houses, trees, cars, etc.) in an image instead of simply classifying individual pixels. Many studies have shown that object-oriented image analysis (OBIA) using medium- and high-resolution satellite images surpasses the traditional pixel-based classification in urban settings [70,71,72,73,74,75]. Object-oriented image analysis (OBIA), sometimes called image segmentation, is the process of dividing an image into spatially adjacent, non-overlapping homogeneous regions (also known as objects) based on color, shape, and scale parameters. This method can be defined as splitting an image into spatially continuous, non-overlapping homogeneous areas (also known as objects) based on color, shape, and scale parameters. In addition, objects created on the basis of spatial information correspond more to real structures or areas on the ground than to individual pixels [76]. Their main advantage is that the decision-making rules are usually determined by the knowledge of a human analyst, rather than computer algorithms [55], and merging different types of data allows for increased accuracy [70]. In the study [77], 13 observation methods were compared, and it turned out that in all cases, object-based classification methods turned out to be slightly better than pixel-based classification methods based only on spectral data.

In particular, a number of studies have shown that OBIA is successfully applied to SPOT data for various purposes [78.79,80,81,82,83,84,85], and in 2014 [86] tested two object-based classification methods (KNN and SVM), and in 2014 [86] tested two object-based classification methods (KNN and SVM SVM) and found that both methods work better than pixel-based (DT) methods for LULC mapping. The literature [87] clearly shows the advantages of using object-oriented methods of classifying knowledge in images of the urban environment of SPOT 5 compared with pixel methods. Among the several methods compared, the first one had the highest accuracy in creating and highlighting significant objects such as roads and buildings. [75] revealed an improvement in OBIA's ability to define city boundaries on a regional scale using SPOT data. [88] demonstrated the advantages of an object-oriented approach compared to pixel-based forest fragmentation assessment. Statistics Sweden (2008) used OBIA and SPOT 5 rule-based data to classify urban green spaces, and the Swedish Environmental Protection Agency used SPOT 5 data [89]. The data classify natural types [89].

Image analysis and classification at the object level are image processing techniques focused on analyzing and interpreting image content based on objects rather than individual pixels. This process goes through a number of stages:

1. image segmentation;
2. extraction of features of objects;
3. classification of objects.

Let's give a brief description of each of these stages.

Image segmentation - This is the process of splitting an image into separate segments or areas in order to simplify analysis. In the context of computer vision and image processing, this means dividing an image into groups of pixels that have similar characteristics or have a uniform structure. The purpose of image segmentation includes [90]:

1. Selection of objects. Segmentation helps to highlight specific objects or areas of interest in an image. This can be useful, for example, when automatically recognizing objects such as cars, faces, or others.
2. Improved analysis. Dividing the image into segments makes it easier to analyze each area independently. This is useful when studying the properties of different parts of an image or when applying different processing methods to each segment.
3. Simplification of machine learning tasks. In machine learning tasks such as training a model for object recognition, segmented images can be used to train a model at the segment level, which can improve accuracy and efficiency.

There are several methods for image segmentation, including threshold segmentation, clustering, object boundary-based methods, and deep learning, including semantic and instance segmentation.

1. Threshold segmentation: Based on applying a threshold for the brightness or color of pixels to separate them into objects and background.
2. Clustering: Groups pixels based on their similarity in the color or texture space.
3. Semantic segmentation: Assigns a class label to each pixel, which allows to select segments corresponding to specific objects.
4. Instance segmentation: Differs in that it distinguishes not only classes of objects, but also each individual instance of an object.

Extracting features of objects (Feature Extraction) — This is the process of highlighting the characteristic features or properties of objects in an image or in other types of data. These features represent information that can be used to describe objects and, often, for subsequent analysis or data processing. Feature extraction plays an important role in pattern recognition tasks, object classification, and other scenarios. Some key aspects of this process include [90]:

1. Feature selection, which includes determining which characteristics of objects or areas of the image will be extracted. These features can range from textural features and color characteristics to the shape and size of objects.
2. Data Transformation: After selecting features, they can be extracted from an image or other data by applying various algorithms and signal processing methods.
3. Feature representation: The resulting features are represented in the form of vectors or sets of numbers that can be used in machine learning algorithms to train models and make decisions.

Well-chosen features can significantly improve the performance of algorithms and models, making them more capable of recognizing and classifying objects.

Classification of objects - This is the process of assigning an object (for example, an image, text, sound, or other data) a certain category or class based on its characteristics and properties. This is one of the key tasks in the field of machine learning and computer vision. The object classification process usually includes the following steps:

1. Data preparation. The source data, such as images or text, is prepared for use in the classification algorithm. This may include scaling, normalization, data transformation, and other preprocessing steps.
2. Feature extraction: The characteristics that will be used for classification are extracted from the data. This may include extracting color characteristics, textures, shapes, numeric values, etc., depending on the type of data.
3. Model selection. The machine learning model that will be used for classification is selected. This can be, for example, a logistic regression model, the k-nearest neighbor method, the support vector machine (SVM) method, neural networks, and so on.
4. Model training. The process of training the model involves the use of pre-marked data. This stage involves transferring the input data and the corresponding class labels to the model so that the model can learn the connections between input features and classes.
5. Testing and evaluation. The trained model is tested on new data that it has not previously seen in order to evaluate its performance and accuracy. Various metrics such as accuracy, completeness, and F-measure can be used to assess the quality of classification.
6. Application. After successful training and testing, the model can be used to classify new data.

Object classification tasks have a wide range of applications and play an important role in automation and data processing. At the same time, two approaches are possible – on the basis of learning with a teacher or on the basis of learning without a teacher.

In Supervised Learning, the model is trained based on labeled data, where a corresponding label or target value is provided for each input example. At the same time, the model seeks to find a mapping between the input data and the corresponding target labels, so that when it encounters new, previously unseen data, it is able to predict or classify the target labels. The following methods of model construction are most often used [91]:

1. Linear regression - used to predict a continuous dependent variable based on one or more independent variables. The main idea is to find a linear relationship between the features and the target variable, which can be expressed as an equation of a straight line or a hyperplane in a larger dimensional space. The process of training a model is to adjust the parameters of the model based on the training data in order to minimize the prediction error. After training, the model can be used to predict the values of the target variable for new observations based on feature values. The quality of a linear regression model is usually assessed using various metrics such as standard error (MSE), coefficient of determination (R^2), mean absolute error (MAE), and others.
2. Support vector machine (SVM) methods perform classification and regression tasks by partitioning the feature space using hyperplanes. The main idea of the SVM method is to find the best hyperplane that best separates the various classes of data in the feature space. In the search process, split it up. A hyperplane is a separating surface that maximizes the distance (gap) between the nearest points of different classes, called support vectors. The hyperplane parameters are searched based on minimizing the loss functional, taking into account the penalty for violating the separation boundary. SVM can use various kernels that allow to build nonlinear separating surfaces in the original feature space by converting data into a higher dimensional space. When classifying satellite images, this method can be used to assign image pixels to a particular class, i.e. in segmentation tasks [92].
3. Decision Trees and Random Forest - Builds decision trees for classification and regression, as well as their combinations into random forests to improve accuracy. The main idea of decision trees is to divide the feature space into regions, in each of which the model makes predictions about the target variable. A random forest creates an ensemble of decision trees, each of which is trained on a subset of training data and using randomly selected features. In a random

forest, two forms of randomness are used: random sampling of observations with replacement (bootstrap) and random selection of features at each split of the tree. This helps to reduce the correlation between trees and reduce overfitting. When it is necessary to make a forecast for a new observation, each tree in a random forest makes its own forecast, and then the forecasts are aggregated (for example, using voting for classification or averaging for regression) to obtain a final decision. A random forest can also be used to segment satellite images.

4. Neural networks are models that can be trained to predict or classify data using layers of neurons and error back propagation algorithms. Neural networks consist of neurons that are grouped into layers. Neural networks usually have three types of layers: an input layer, hidden layers, and an output layer. Each neuron in one layer is connected to neurons in the next layer. These connections have weights that are adjusted during the learning process to achieve optimal network performance. This usually happens using optimization techniques such as stochastic gradient descent. An activation function is applied to each neuron, which determines the output value of the neuron based on the input data and the weights of the connections. Deep learning: Neural networks with multiple hidden layers are called deep neural networks. Depending on the tasks being solved, various neural network architectures are used - multilayer perceptrons (MLP), convolutional neural networks (CNN), recurrent neural networks (RNN) and deep neural networks (DNN). Deep convolutional neural networks are usually used when processing satellite images [93].

In Unsupervised Learning, the model is trained on untagged data, and there are no target labels. The model has to find structures or patterns in the data on its own. In this way, the model seeks to highlight common characteristics or structures in the data, and can also be used to reduce the dimensionality of the data. Clustering methods are most successfully used for processing satellite images. At the same time, the k-means algorithm shows good results. It is used both for preliminary segmentation of the entire image in order to identify various areas of interest, and for segmentation of the areas of interest themselves, for example, to determine the degree of development of agricultural plants in the fields [94].

Clustering methods are algorithms that group data based on their similarity. The k-means algorithm is a clustering method that is used to divide a dataset into k clusters. The basic idea is to divide the data into clusters in such a way that objects within one cluster are more similar to each other than to objects from other clusters. The number of clusters is set by the user. First, the centers for each cluster are selected in one way or another. Then each data object is assigned to the nearest centroid, thus creating clusters. After assigning objects to clusters, the centroids of the formed clusters are recalculated by calculating the average value of all objects in each cluster. The process of assigning clusters and recalculating centroids is repeated until the centroids are stabilized or until the maximum number of iterations is reached. Various metrics can be used to assess the quality of clustering, such as the sum of the squares of the distances to the centroids, the distance between the centroids, or their ratio of these metrics.

Object analysis and image classification improve the accuracy and contextual understanding of the analyzed data, which makes them more useful for a wide range of tasks in various fields. Segmentation and classification of big data is possible based on the use of neural networks and optimization of their hyperparameters. Almost all modern satellite image processing systems are based on the use of deep learning neural networks, since they allow for high accuracy of segmentation and classification of objects [94].

2.5. Deep neural networks

Deep learning relies on the use of multi-layered neural networks to obtain high-level features from input data. As a result of training, a specific set of features is formed on each layer of such networks, reflecting both local features and general features of the processed data [95]. Semantic segmentation architectures based on convolutional neural networks can specifically extract contextual features and object-level information at several levels and, finally, label each pixel of the input image [96]. They are used in many image analysis tasks, including satellite image processing, medical research, robotics, autonomous vehicles, precision agriculture, etc. [96,97]. In the field of remote sensing, many studies have applied semantic segmentation algorithms to 2D images and even 3D scenes [98]. For example, a fully convolutional network model has been applied to Sentinel-2 and SAR data for slum mapping with learning transfer based on very high resolution optical satellite images (VHR) [99]. CloudNet, a semantic image segmentation model with deep residual learning and atrophic convolution, was proposed to identify clouds and haze in Sentinel-2 images [100]. The DeepUNet network, which is a redesigned U-Net network structure, was used to segment seas and land at the pixel level using manually marked annotations and images from Google Earth [101]. Thus, DL-based models open up new possibilities for object detection, especially in cases where high- and medium-resolution remote sensing images are used.

Convolutional neural networks (CNNs) are a class of neural networks specializing in processing structured data (such as images) in the form of lattices or matrices for computer vision tasks such as image classification, object detection, and image segmentation. They are successfully applied. The main components of convolution neural networks include:

1. Convolutional layers that apply filters (convolution kernels) to an image to extract various features. These layers allow the network to automatically study important image characteristics such as faces, textures, and shapes. On each layer, so-called "feature maps" are formed, which are processed by other filters on the next layer of the network.
2. Pooling layers - reduce the dimension of the feature space by removing redundant data and simplifying calculations.
3. Fully connected layers are used for classification or regression based on extracted features. There are also networks in which fully connected layers are missing and replaced with convolutional layers.
4. Activation functions - applied after each layer to add non-linearity to the network. The ReLU (Rectified Linear Unit) activation function is most often

used between layers, and the sigmoidal activation function is usually used on the output layer.

When training the network, the loss function is minimized. This function evaluates in one way or another the difference between network forecasts and true labels. The loss function is constructed depending on the nature of the problem being solved. The most commonly used loss functions are the standard error (MSE) and the cross-entropy function. In segmentation problems, the loss function is formed based on the Jacquard coefficient of the IoU metric [102].

Since the optimization problem is solved during training, various optimization algorithms can be used. These algorithms update network parameters during the learning process to minimize the loss function. As a rule, algorithms based on stochastic gradient descent are used, such as the Adam optimizer [102].

Another method that can be used to speed up and normalize the learning process of neural networks is Batch Normalization. This method of normalization of activations in neural networks, which was proposed in 2015. It is used to stabilize and accelerate the learning of deep neural networks by normalizing the input data of each layer. The basic idea is to normalize the activations of each layer before transferring them to the next layer. This helps prevent explosive growth of gradients and accelerates learning convergence. The main components of Batch Normalization include:

1. Calculation of Batch Statistics: The average and standard deviation of activations are calculated for each mini-data packet.
2. Normalization of activations: Activations of each layer are normalized by subtracting the mean and dividing by the standard deviation, then scaling is applied using the scaling parameter and adding an offset using the offset parameter.
3. Parameter update: The scaling and offset parameters are trained along with the rest of the network parameters in the process of error back propagation.

Batch Normalization is often applied to the results of a convolution operation in convolutional layers or to the results of a fully connected layer in neural networks. It helps to speed up learning, improve learning stability, and usually leads to better generalizing ability of models [102].

After normalization of the learning process, it is necessary to avoid the process of retraining, for this the regularization method is used. This is another method in machine learning that is used to prevent overfitting a model by limiting its complexity or the size of the weights. The main idea of regularization is to add an additional term to the loss function of the model, which penalizes large values of weights or their complexity. There are two main types of regularization [102]:

1. L1 regularization (Lasso): In this method, a penalty is added to the loss function, proportional to the absolute value of the model weights. L1 regularization is also called the Lasso method (Least Absolute Shrinkage and Selection Operator). It can lead to sparse weights because it can reset some weights, making the model more interpretable.
2. L2 regularization (Ridge): In this method, a quadratic penalty is added to the loss function, proportional to the square of the weights of the model. L2 regularization is also called the Ridge or Tikhonov regularization method. She aims to make the model's weights smaller and prevent them from overfitting.

Regularization is often used in conjunction with other machine learning methods such as linear regression, logistic regression, or neural networks. It helps to improve the generalizing ability of models and prevent them from overfitting on training data [102].

Deep learning methods also include the so-called Transfer Learning. This is a machine learning method that allows to use the knowledge gained from training a model on one task to improve performance or speed up model training on another task. The basic idea is to use the pre-trained weights of a model trained on a large dataset and adjust them on a new dataset associated with a new task. Key Aspects of Transfer Learning:

1. Pre-training: First, the model is trained on a large dataset and gains knowledge about the features and dependencies in the data.

2. Knowledge transfer: After that, the knowledge gained during the preliminary training is transferred or transferred to a new task. This may include the use of pre-trained neural network weights or feature extraction functions.
3. Model Setup: The model is then configured or retrained on a new dataset to perform a specific task. This may include changing the last layers of the model or using a frozen layer learning technique.

Transfer Learning allows to use the knowledge gained on one task to improve the performance of the model on another task, especially if a small amount of training data is available for a new task. This method allows to significantly reduce the cost of training new models and improve the performance of models on new tasks, especially in conditions of a limited amount of available data.

2.5.1. Encoder – decoder architectures

Encoder-decoder architectures are a class of neural networks that consists of two main components - an encoder and a decoder. These architectures are widely used in various fields of machine learning, such as machine translation, text generation, image segmentation, and others [103].

Encoder:

1. The encoder accepts data as input and converts it into some hidden representation or code.
2. Usually, the encoder consists of several layers of neural networks that gradually reduce the dimension of the input data and extract their features.
3. Recurrent neural networks (RNN), convolutional neural networks (CNN), or combinations thereof can be used in the encoder to process sequential data such as text or time series.

Decoder:

1. The decoder takes the hidden representation received from the encoder and decodes it back into the output data.

2. The decoder also consists of several layers of neural networks that gradually increase the dimension of the data to the original dimension of the input data.
3. It can also use recurrent layers to model the dependencies between input and output data, especially in the case of sequence generation.

The mechanism of attention (Attention Mechanism):

1. Some encoder-decoder architectures add an attention mechanism that allows the network to focus on different parts of the input data at different times.
2. This helps to improve the output quality, especially in tasks where it is necessary to process long sequences or variable-length inputs.

Encoder-decoder architectures are used to solve a wide variety of tasks – both for image segmentation, machine translation, and text generation. These architectures are highly flexible and can be adapted to different tasks and data types. Among the most successful architectures that provide relatively high quality ratings are the following:

1. Seq2Seq (Sequence-to-Sequence) models are used in machine translation, question-answer, text generation and other tasks where it is necessary to convert one sequence into another.
2. Models for text generation that are based on recurrent elements such as LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) that convert hidden sequence representations into text.
3. SegNet and U-Net architectures that have shown good quality metrics in the image segmentation task, where the input images are converted to segmented masks.

2.5.2. Neural network architectures for image segmentation

Semantic image segmentation is the allocation of local image regions corresponding to different classes of objects. Although methods and algorithms for classifying objects in images are developing rapidly, this problem has not yet been completely solved. On the other hand, there is no single generally accepted approach that could form the basis of most algorithms. There is also no general algorithm that provides the best segmentation for any image.

Currently, there are many methods of semantic image segmentation based on the use of convolutional neural networks (CNN). In general, such methods provide fairly good performance and segmentation accuracy for relatively small images. At the same time, various CNN architectures are used to classify and tightly label these images. However, these neural network image processing methods have certain disadvantages and are far from perfect. It should also be noted that the computational cost of segmentation is high due to the high resolution of satellite images of the earth's surface. Therefore, it is very important to develop methods that reduce computational costs and improve the quality of segmentation.

Currently, there are no strict rules for the configuration of convolutional neural network (CNN) structures - this includes choosing the number of layers, sizes and number of feature maps, as well as the sizes of convolution matrices, learning algorithms, etc. When developing CNN structures, it is important to keep in mind that a small number of network parameters can reduce classification accuracy. At the same time, a large number of parameters can increase computational complexity and does not always lead to an improvement in the classification ability of the network.

Semantic segmentation in computer vision consists in assigning a semantic label to each associated area of an image. Almost all modern CNN architectures for image segmentation follow the principles outlined in [104]. The main idea is to change the traditional CNN classification so that the output is not a probability vector, but a probability map of classes. As a rule, the standard CNN is used as an encoder that generates feature maps for various levels of image decomposition. The encoder is followed by a decoder that scales feature maps to the original spatial dimensions of the input image. Then a heat map is obtained for each class. Deep semantic segmentation networks are usually based on the principles of full convolution and encoder–decoder architectures [124].

Typically, the encoder is a sequence of convolutional layers followed by batch normalization (BN) and rectified linear activation function (ReLU). The convolution blocks are followed by a pulling layer. In fact, the encoder is an ordinary convolutional network trained to classify the input image. The decoder has the same number of layers and performs the function of interpolating the encoder output. At the last level of the decoder, a 1×1 convolution followed by a sigmoidal activation function is usually used to form the output segmented image.

U-Net [105] and MobileNet [106] are two different neural network architectures designed to solve different problems. U-Net is usually used for image segmentation. The architecture includes convolutional layers for feature extraction and transposed convolutional layers for increasing dimensionality and creating detailed segmented maps.

In the Unet architecture, when using the pooling operation, the 2×2-pixel area maximization method is used. After passing through several successive layers of convolution and pooling, the input image is transformed into abstract feature maps, which are the output data of the corresponding encoding blocks.

The Unet network can be considered as a modified version of the first one, which combines the output data of the decoder layers with feature maps from the encoder at the same level. In this case, interpolation in the decoder layers is performed using transposed convolution [107]. This architecture has shown a significant increase in the accuracy of segmentation of images of various natures, as well as the ability to learn from a small amount of data. The disadvantages of Unet are relatively low performance and high resource consumption. These disadvantages are associated with the rather complex and resource-intensive architectures of the encoders used, such as ResNet [108], Inception [109], EfficientNet [110].

MobileNet, on the other hand, is designed to classify images with a minimum number of parameters. Its lightweight architecture makes it suitable for use on mobile devices and embedded systems. U-Net uses MobileNet as an efficient encoder to extract functions from input images. Thanks to its lightweight architecture, MobileNet allows to quickly process images and extract important functions. MobileNet replaces the standard convolutional layers in the U-Net encoder. This reduces the number of parameters and calculations, which is useful for resource-intensive scenarios. MobileNet is used as an encoder in U-Net when high performance is needed in resource-constrained environments.

Initially, the U-Net neural network architecture was developed for semantic segmentation of medical images. With its help, certain types of cells were isolated in images obtained from microscopes. The same architecture was used to segment organ abnormalities in tomographic images. However, then this architecture began to be successfully used for segmentation of other images, including satellite images. The main idea of U-Net is to use a fully convolutional architecture, which works equally well both for encoding (reducing the dimension) of an image and for decoding (increasing the dimension) of the resulting representation in order to restore segmented images. The main features of the U-Net architecture include [105]:

1. Convolutional blocks: The architecture consists of a sequence of convolutional blocks, including convolution, activation function (usually ReLU) and pooling operation. These blocks are used to extract features from the input image.
2. Encoder Path: The input image is consistently reduced in size using convolution and pooling operations, which allows to extract more and more abstract features.
3. Decoder Path: After reaching the minimum image size, the size is gradually increased using transposed convolution and concatenation operations with the outputs of the encoder blocks, which allows to restore spatial resolution and perform segmentation.
4. Residual connections (Skip Connections). To improve the transmission of information between the encoder and the decoder, transmission connections are used that transmit signs from lower levels directly to the corresponding layers of the decoder.
5. Loss function. Usually, the cross-entropy loss is used as a loss function, especially for the binary segmentation problem, or the mean squared error for the multi-class segmentation problem.

U-Net demonstrates high efficiency in solving image segmentation problems due to its special architecture, which allows to extract both local and global features from images, while preserving spatial information and details. However, this architecture is very resource intensive. It requires both large amounts of memory and powerful graphics accelerators, even when processing medium-resolution images.

In this paper, it is proposed to use a neural network based on the principles of the U-Net architecture for semantic segmentation of satellite images. At the same time, the main attention will be paid to reducing the requirements for the necessary computing resources, while the segmentation accuracy should not decrease. The proposed method is discussed further in the third chapter of the work.

Conclusion to Chapter 2

1. It is proposed to use a neural network for atmospheric correction. This is due to the fact that data (images) obtained from data access hubs are usually provided with atmospheric correction. However, often the available data do not always have an atmospheric correction. Therefore, a method is proposed that allows automating the process of atmospheric correction of "raw" satellite images using a simple convolutional neural network implementing the encoder -decoder architecture. Images without atmospheric correction are received at the input of such a network, and the result of its operation will be images with atmospheric correction. The network should be trained on a dataset formed from images of the earth's surface with atmospheric correction already performed and images of the same areas without it. This approach will allow for atmospheric correction for those satellite data for which there is no atmospheric correction.
2. To classify crops grown on agricultural lands, it is proposed to use indices of a set of different vegetation indices. This is due to the fact that these indices differ for different crops, and also reflect the degree of vegetation development. Thus, vegetation indices can be used in the future as informative signs for the crop type recognition system. In addition, vegetation indices can be used for preliminary identification of agricultural land.
3. To solve the problems of atmospheric correction, segmentation of satellite images and classification of crops, it is proposed to use neural networks based on various architectures. This is due to the good accuracy indicators achieved with their help. It should be noted that when implementing them, it is necessary to reduce the requirements for computing resources, but at the same time, the accuracy of the results, at least, should not decrease compared to existing solutions.

CHAPTER 3. DEVELOPMENT OF METHODS FOR MONITORING THE TERRITORY BASED ON SATELLITE IMAGES

3.1. General structure of the system for monitoring areas of the Earth's surface

Based on the analysis carried out in Chapter 2, the following structure of the satellite data processing system for monitoring the region of the earth's surface is proposed, shown in Figure 3.1.

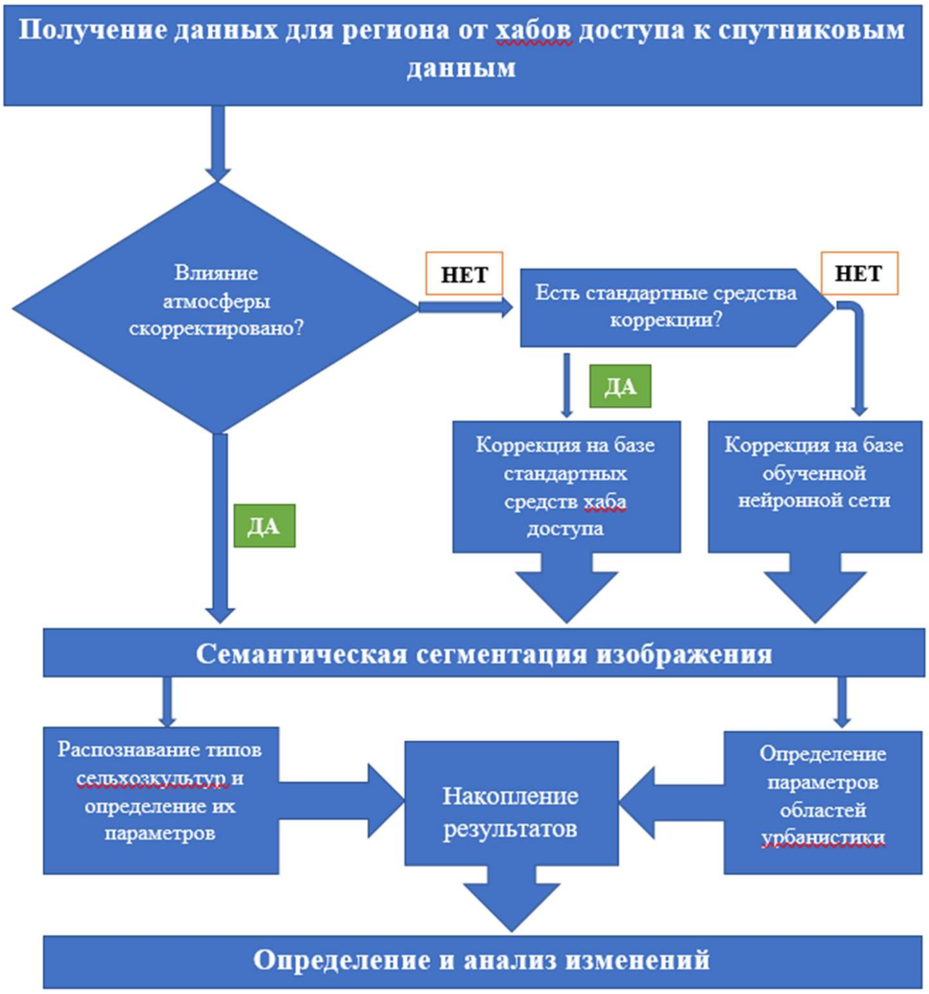


Figure 3.1. Structure of the Earth surface region monitoring system

The proposed structure reflects the main components of the monitoring system – data acquisition using two methods of atmospheric correction, as well as components implementing segmentation and classification of segmented areas, and their further analysis.

3.2. Monitored regions

To evaluate the various methods of detecting changes presented in this dissertation, the cities of Uzbekistan in the Ferghana Valley were selected as places for research. As the largest cities in Uzbekistan, Tashkent, Ferghana, Andijan and Namangan have experienced rapid changes in their urban structure. This high rate of expansion makes them attractive candidates for urban change detection research using remote sensing images.

Tashkent is one of the centers of Central Asia, the capital of the sovereign Republic of Uzbekistan. Tashkent is located in the northeastern part of the republic, in the observation zone in the valley of the Chirchik river, at an altitude of 440-480 meters above sea level and occupies about 43,500 hectares.

Figure 3.2. The city of Tashkent, captured by the Landsat satellite (Google Earth Engine platform)

The city of Ferghana, located in the south of the Ferghana Valley, is one of the ngest cities in Uzbekistan. Established in 1876 as a result of the annexation of the Kokand Khanate to the Russian Empire, the city, named New Margilan, was built 12 kilometers from Margilan and became the administrative center of the Ferghana region.

Figure 3.3. The city of Ferghana, captured by the Landsat satellite (Google Earth Engine platform)

Andijan is an ancient city located in Uzbekistan, in the south-east of the Ferghana Valley, near the border with Kyrgyzstan. The administrative center of the Andijan region of the sovereign republic. Andijan is 360 km away from the capital Tashkent.

Figure 3.4. The city of Andijan, captured by the Landsat satellite (Google Earth Engine platform)

Namangan is one of the oldest cities. The approximate date of its foundation is 1610. The relief of the city is mostly flat. The city's land surface is inclined from north to south and from west to east; the southern part of the territory is subtropical. In summer, there is a sharp increase in air temperature. Namangan is located in the northern part of the Ferghana Valley, 200 km southeast of Tashkent (about 300 km by road).

3.3. Methods for obtaining satellite data

Before choosing a data source for a regional monitoring system, it is important to consider factors such as data availability, cost, quality, and compatibility with existing tools and software. In this study, data will be obtained from two main sources: the Google Earth Engine and the Sentinel Hub platform.

3.3.1. Getting data from Google Earth Engine in interactive mode

Google Earth Engine (GAE) offers a wide range of datasets and tools that can provide various types of information for monitoring the territory of Uzbekistan. To get information from Google Earth Engine, need to register and log in to the platform, select an area of interest (AOI) for Uzbekistan, search for relevant datasets and process the data using GEE image processing functions. To get information from GEE for monitoring the territory of Uzbekistan, some steps may follow:

1. Must register and log in to the Google Earth Engine platform using a Google account.

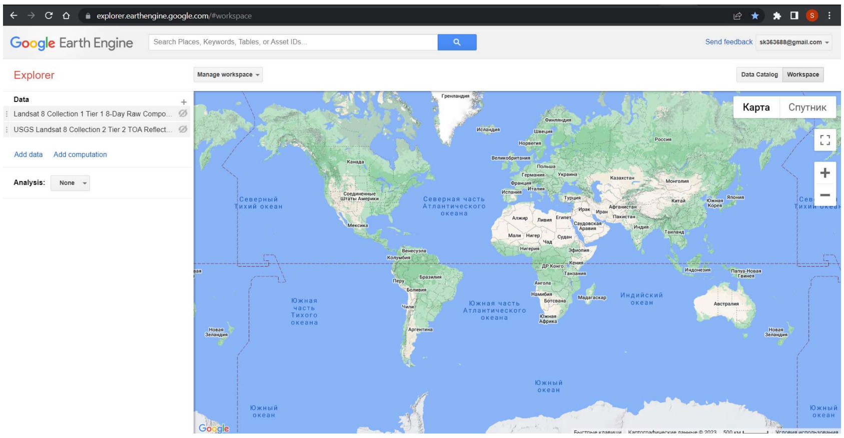


Figure 3.5. The workspace of the Google Earth Engine platform

2. It is necessary to select a zone of interest for Uzbekistan. This can be done by drawing a polygon over the desired area using the Draw Shape tool in the GEE user interface.
3. After that, should search for datasets containing relevant data for the selected area of interest. This can be done by using the "Search" tab in the GEE user interface and filtering by keywords, data type and other criteria.

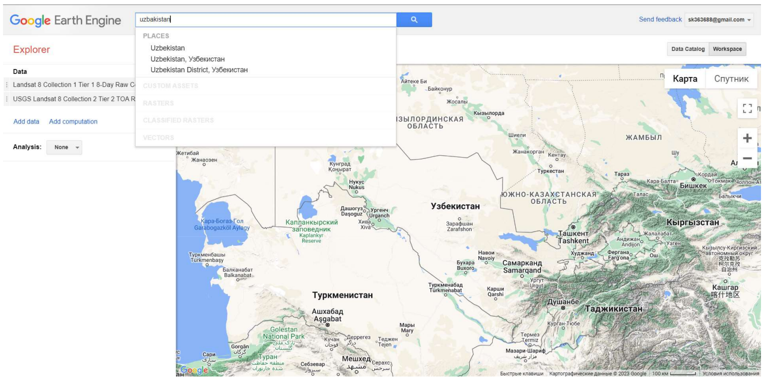


Figure 3.6. On the platform, the field of scientific research can be found through a search engine or through a graphical assistant

4. Select the necessary datasets and add them to the GEE workspace. This can be done by clicking on the dataset and then clicking "Add to Map".

5. Process the data using GEE image processing functions. This can be done by writing JavaScript and Python code on the Code Editor tab in the GEE user interface. The code can be used to filter, process, and visualize data.

6. Finally, the processed data should be exported for further analysis. This can be done by using the Export tab in the GEE user interface and selecting the desired export format and options.

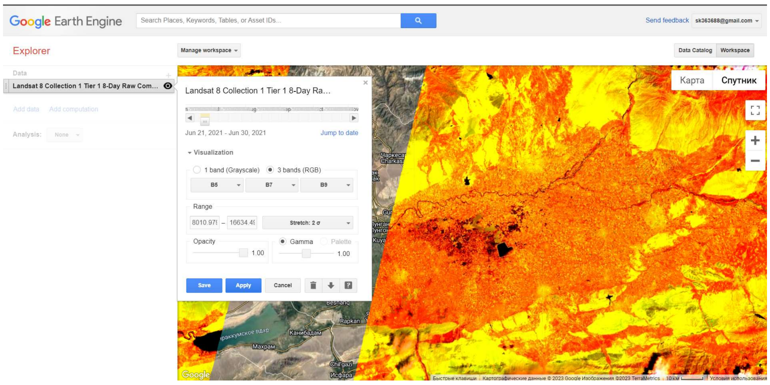


Figure 3.7. Some settings can be made on the research object on the platform. For example, spectral ranges and auto-correction service

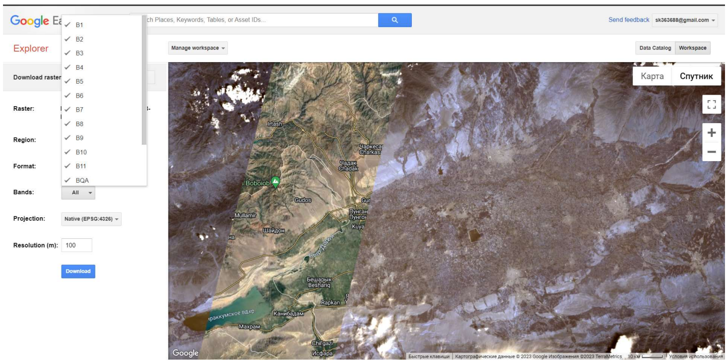


Figure 3.8. It is possible to pre-configure and download the necessary satellite data from the platform

3.3.2. Obtaining data from Google Earth Engine in automatic mode

Automated data collection from Google Earth Engine means using software tools to extract and download geospatial data from the Google Earth Engine cloud platform without manual intervention. Google Earth Engine provides extensive geospatial datasets and powerful analysis tools available through APIs that automate the data collection process. Google Earth Engine provides a wide range of geospatial data that can be used for a variety of applications, including agricultural land analysis, vegetation change monitoring, disaster risk assessment, and more. As an example of data analysis for Uzbekistan, let's consider a detailed algorithm for working with the Google Earth Engine API:

1. Installing and configuring the API:
   - It is necessary to check that have the earth engine api library for Python installed.
   - Need to register with Google Earth Engine and create an account with API access.
2. Importing the library and initializing the API:
   - Import the Python Earth Engine API library: import ee.
   - The API must be initialized using the ee.Initialize() command.
3. Definition of the area of interest (AOI):
   - Define the geographical area of Uzbekistan using a geometric object (for example, a rectangle) by specifying coordinates.
4. Data selection:
   - Need to select the data that want to analyze. For example, it could be a Landsat dataset for monitoring vegetation changes.
5. Data filtering:
   - To select information related only to Uzbekistan, apply filters by time and region.
   - Cloud filters can be used to exclude cloud scenes.
6. Data analysis:
   - Analysis operations such as vegetation index calculation (NDVI, NDWI), classification, dynamic transformation, etc. can be applied
7. Visualization of the results:
   - Visualization of results, for example, using graphs or maps.
8. Data export (optional):
   - If necessary, the data can be exported to the desired format for further use in other applications.

engine_1.py

```python
import ee
import folium

# Инициализация API Google Earth Engine
ee.Initialize()

# Определение области интереса (Узбекистан)
aoi = ee.Geometry.Polygon(
        [[[55.92825871426012, 41.24578110552716],
          [55.92825871426012, 37.15377917845855],
          [73.23130695676012, 37.15377917845855],
          [73.23130695676012, 41.24578110552716],
          [55.92825871426012, 41.24578110552716]]])

# Загрузка коллекции изображений Landsat
collection = ee.ImageCollection('LANDSAT/LC08/C01/T1_TOA') \
    .filterBounds(aoi) \
    .filterDate('2022-01-01', '2022-12-31') \
    .sort('CLOUD_COVER') \
    .first()

# Визуализация изображения на карте
map = folium.Map(location=[39.5, 65.0], zoom_start=6)
map.addLayer(collection, {'bands': ['B4', 'B3', 'B2'], 'min': 0, 'max': 0.3}, 'Landsat')
map.addLayerControl()
map
```

Figure 3.9. Sample Python code for downloading and visualizing Landsat data for Uzbekistan using the Google Earth Engine API

This is an example of downloading and visualizing a Landsat image for Uzbekistan using the Google Earth Engine API. Package parameters, filters and other parameters can be customized according to needs.

3.3.3. Receiving data from the Sentinel Hub in interactive mode

Sentinel Hub is a cloud—based platform that provides access to a wide range of satellite data, including Sentinel-1, Sentinel-2, Sentinel-3 and other missions. The platform offers various tools for data visualization, processing and analysis, which makes it a useful tool for monitoring the environment and natural resources. To receive information from the Sentinel Hub for Uzbekistan, follow these steps:

1. Should register and log in to the Sentinel Hub platform using a valid account.

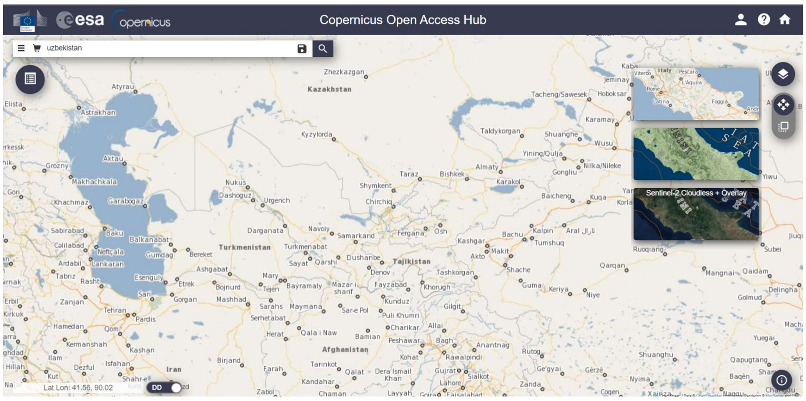


Figure 3.10. After registration, the Sentinel Hub workspace opens

2. Select the area of interest (AOI) for Uzbekistan. This can be done by specifying the latitude and longitude coordinates of the desired area or by drawing a polygon using the platform's map interface.
3. It is necessary to search for available data for the selected area of interest. This can be done using the platform's data discovery tools, which allow to filter datasets based on date range, sensor, and other parameters.

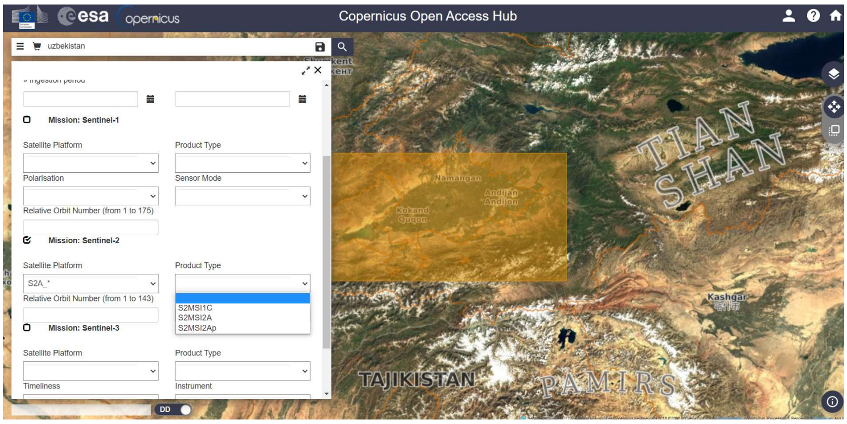


Figure 3.11. By selecting the required field, configure additional filters offered by the platform and select which satellite receive

4. Selection the desired datasets and visualize the data using the platform's image processing tools. This can be achieved by applying filters, adjusting the contrast of the image, and using other methods to improve the visual representation of the data.

5. It is necessary to export the data for further analysis. This can be done by uploading the data in the desired format or integrating the data with other analysis and visualization software.

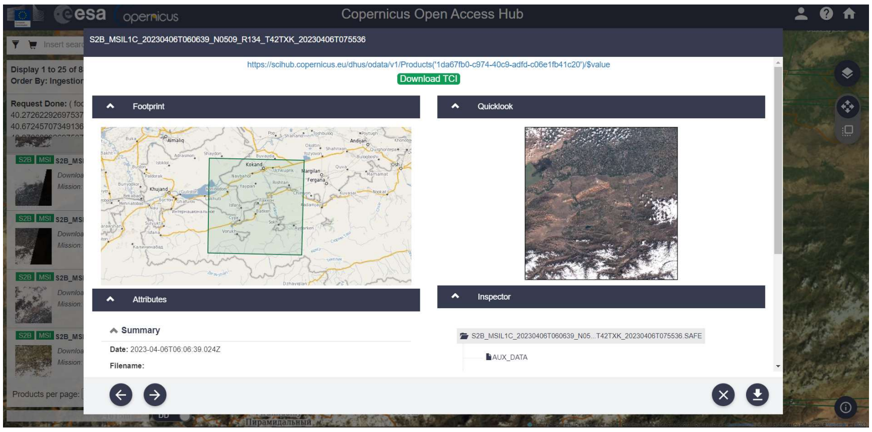


Figure 3.12. Before downloading, check the desired area again and download it

3.3.4. Receiving data from Sentinel HUB in automatic mode

To receive data from the Sentinel Hub in automatic mode, use their API, which provides access to a wide range of geospatial data, including images from Sentinel satellites. An API (Application Programming Interface) is an interface that allows software to interact with other programs or services. In the case of geospatial data, the Sentinel Hasp API allows developers to access various datasets about geographical features, satellite images, metadata, and other information through programmatic queries.

An example of an algorithm for working with the Sentinel Hasp API to obtain data on geographical objects and satellite images for Uzbekistan:

1. Registration and receipt of the API key:
   - Need to go to the Sentinel Hub website and register an account.
   - Get an API key (instance ID) that will allow to use the Sentinel Hub API.
2. Import the necessary libraries:
   - Need to install the Sentinelhub library for Python, if it is not already installed.

- To work with the API in a Python script, need to import the necessary classes and methods from Sentinelhub.

3. Definition of the area of interest (AOI):
   - It is necessary to select the geographical region of Uzbekistan from which information should be obtained. It can be defined as a geometric object (for example, a rectangle or polygon) using coordinates.
4. Request formation:
   - A request is sent to the Sentinel Hub API specifying the necessary parameters, such as the data type (for example, Sentinel-2 images), time interval, area of interest, image dimensions, and other parameters.
5. Sending a request:
   - The prepared request is sent to the Sentinel Hub API using the API key and request parameters.
6. Receiving data:
   - The data is received as a response to the request. These can be satellite images, metadata, or other information about geographical objects in a certain area and in a certain period of time.
7. Data processing and analysis:
   - The received data is processed and analyzed according to the set goals. This can include image processing, feature extraction, time series analysis, and more.

```python
from sentinelhub import SHConfig, BBox, CRS, SentinelHubRequest, DataCollection
import matplotlib.pyplot as plt

# Инициализация конфигурации API
config = SHConfig()
config.instance_id = 'YOUR_INSTANCE_ID'  # Замените YOUR_INSTANCE_ID на ваш идентификатор экземпляра

# Определение области интереса (AOI)
bbox = BBox([55.0, 37.0, 73.0, 45.0], CRS.WGS84)

# Формирование запроса к API Sentinel Hub
request = SentinelHubRequest(
    data_folder='./data',
    evalscript='// Оценочный скрипт Sentinel Hub',
    input_data=[
        SentinelHubRequest.input_data(
            data_collection=DataCollection.SENTINEL2_L1C,
            time_interval=('2022-01-01', '2022-01-10'),
            mosaicking_order='leastCC'  # Порядок мозаики с наименьшим облачным покрытием
        )
    ],
    bbox=bbox,
    size=(512, 512),
    config=config
)

# Получение данных
response = request.get_data(save_data=True)
```

Figure 3.13. Sample code for obtaining Sentinel-2 images for Uzbekistan using the Sentinel Hub API

This code sends a request to the Sentinel Hasp API to receive Sentinel-2 images for Uzbekistan over a certain time range and visualizes the resulting image using the matplotlib library.

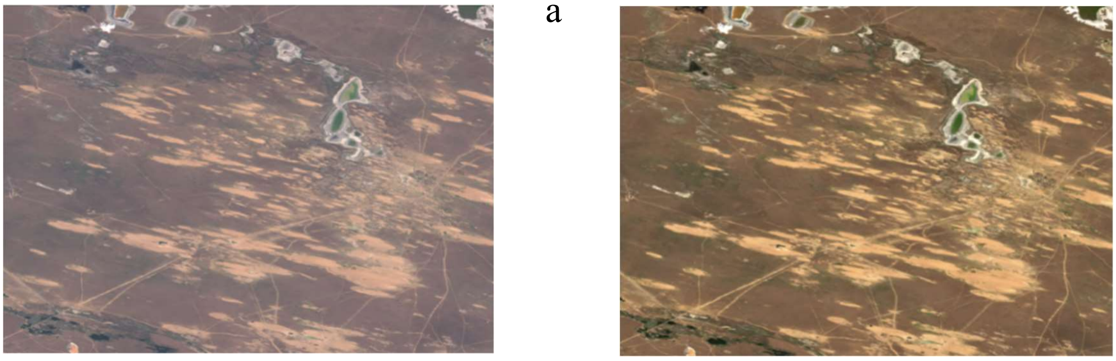
3.4. Methods of satellite image preprocessing

Currently, data from most satellites are publicly available, but only a small part of them are data with previous atmospheric correction. Users who have access to data from a particular satellite can perform atmospheric correction of the necessary data using appropriate application programs. However, this processing is usually performed interactively for each image of a certain area.

Correction of atmospheric distortions of data obtained by remote sensing of the Earth is a critical stage of preprocessing. It compensates for the differences between the solar radiation reflected from the surface and the true radiation recorded on board the spacecraft. These differences depend on many factors, including the angle of incidence of sunlight, the position and viewing angle of the spacecraft, the composition and humidity of the atmosphere, and others. Satellite images are often processed without atmospheric correction. However, the introduction of this correction helps to improve the reliability of satellite image processing results.

Many atmospheric correction algorithms are available as part of the data center software for various satellite families. However, atmospheric correction is not performed for all data received from satellites. Users can perform their own data preprocessing, including atmospheric correction, using specialized application programs.

Most satellites provide multispectral images of the Earth. The data received from Sentinel-2 satellites has already been partially processed at several levels. Two of them are used in this work, namely L1C and L2A. Images of the L1C level are images that have undergone orthocorrection. The images obtained at the L2A processing level underwent both ortho and atmospheric correction. Users who have access only to L1C level data can independently perform atmospheric correction of the necessary images using specialized applications located on the Sentinel access hub. However, such processing often requires interactive interaction for each image individually, which makes it difficult to automatically process large sets of such images. An example of the same image in the visible spectral range at the L1C and L2A levels is shown in Figure 3.14.



a b

Figure 3.14. Images at levels 1C and 2A: (a) Incorrect image — level L1C (b) Image with atmospheric correction — level L2A

The GEE platform accumulates data received from a variety of satellites, and at the same time allows to select any of them. Not all the data obtained in this way have atmospheric correction. At the same time, as a rule, there may be no means for conducting atmospheric correction for these data. Therefore, in order to carry out atmospheric correction of data obtained from various sources, a method is proposed that allows this correction to be made. The method is based on the use of a neural network with an encoder–decoder architecture. The available data of the L1 and L2 levels obtained from the Sentinel-2 platform is used as a dataset for network training.

3.4.1. Neural network for atmospheric correction of satellite images

The proposed method makes it possible to automate the process of atmospheric correction of "raw" satellite images using a simple convolutional neural network. Images without atmospheric correction are received at the input of this network, and the result of its operation will be images with atmospheric correction. The most suitable network architecture for such conversion is the encoder–decoder architecture. The structure of the proposed neural network is shown in Figure.3.15. The encoder contains only three coding layers. The structure of the coding layer is shown in Figure. 3.15. In fact, the encoder is an ordinary convolutional network trained to classify the input image. The decoder has the same number of layers and performs the function of interpolating the encoder output. The decoding layer shown in Figure 3.15 is a reverse convolution followed by batch normalization.

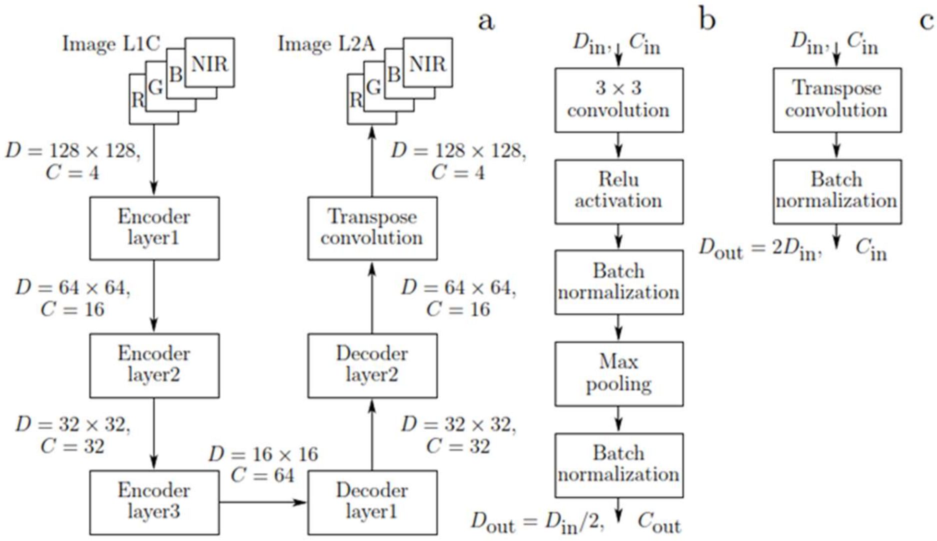


Figure 3.15. (a) The structure of the proposed neural network. (b) The coding layers. (c) Decoding layer. D indicates the size of the image, C indicates the number of filters

The initial data set for training and testing a neural network is a subset of satellite images from the L1C and L2A levels obtained for several regions of the Earth at different times of the year. The analysis uses data obtained from spectral channels B04 (red), B03 (green) and B02 (blue) in the visible range, as well as data from channel B08 (near infrared) of the spectral range. The preprocessing algorithm for atmospheric correction, shown in Figure 3.15, begins with the alignment of the sizes of all image channels. After that, each image is divided into 64 parts, and each part is normalized in brightness. This process creates 64 four-channel images. Next, the resulting set of images is randomly divided into training, verification and test datasets, which make up 80%, 10% and 10% of the entire dataset, respectively. Then the network is trained, which is then used for atmospheric correction

Corrected images are fed to the input of the trained neural network. The result of processing each such image is 64 parts of the output image. From these parts using the post-processing algorithm shown in Figure 3.16 a full-size image with atmospheric correction is compiled.

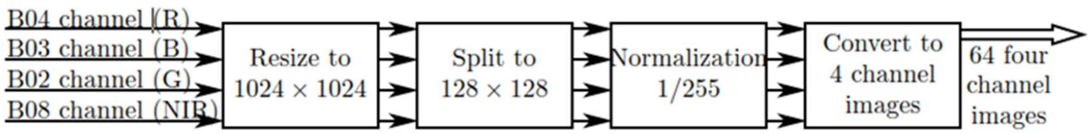


Figure 3.16. Data preprocessing algorithm

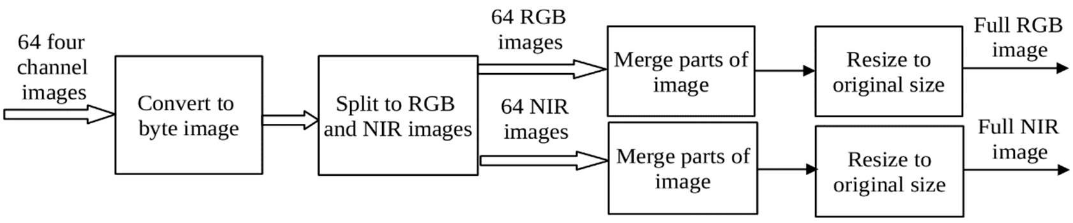


Figure 3.17. Algorithm for post-processing of output data

Using the proposed neural network makes it possible to carry out atmospheric correction and unify images obtained from different satellites. The procedure for training the proposed network and the results of its use are described in Chapter 4.

3.5. Neural network for semantic segmentation of satellite images

As noted in Chapter 2, among networks for semantic segmentation, networks based on the U-Net architecture show better segmentation results compared to other architectures. Therefore, in this paper it is proposed to use this architecture as a basic one. However, this network requires significant computing resources for its operation, and does not have too high performance, which is especially important when processing high-resolution images.

Images obtained by remote sensing of the Earth have a high resolution, often exceeding 2000x2000 pixels, while most convolutional neural networks, including U-Net, are designed to work with images of 256×256 pixels. When dividing large images into smaller fragments, the processing time increases in proportion to the number of fragments. For efficient segmentation of large images, it is necessary to increase network performance while maintaining the necessary accuracy.

One way to improve the performance of this architecture is to use high-performance encoders. Currently, the MobileNet network [111] is one of these encoders. It reduces memory consumption for calculations, while maintaining high accuracy of forecasts. This pre-trained network can even be used on mobile devices. The paper proposes to modify the architecture of the U-Net network for segmentation of satellite images, where the MobileNet network is used as an encoder. The proposed architecture is named MobileNet-Unet and is shown in Figure 3.18.

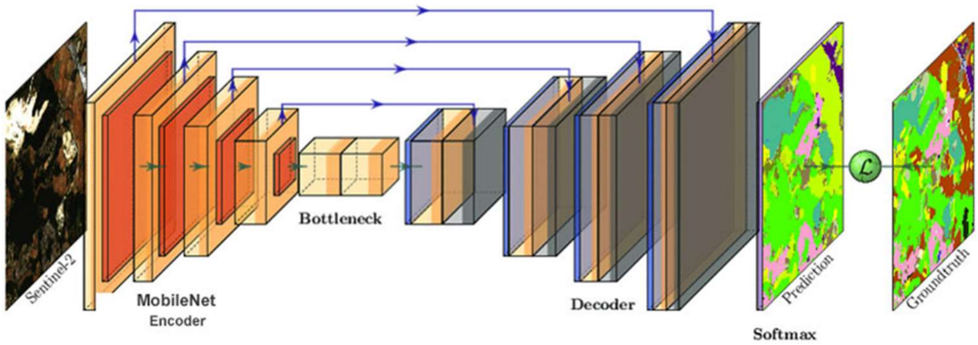


Figure 3.18. MobileNet-Unet architecture

MobileNet, used as an encoder, is a convolution network specifically designed for use, for example, on mobile devices with limited computing resources. It was introduced by Google researchers in 2017. The main idea of MobileNet is to use "deepwise separable convolutions", which allow to perform convolutions with fewer parameters than traditional convolutional layers. This allows to reduce the number of calculations and the number of parameters of the model, which makes it easier and faster.

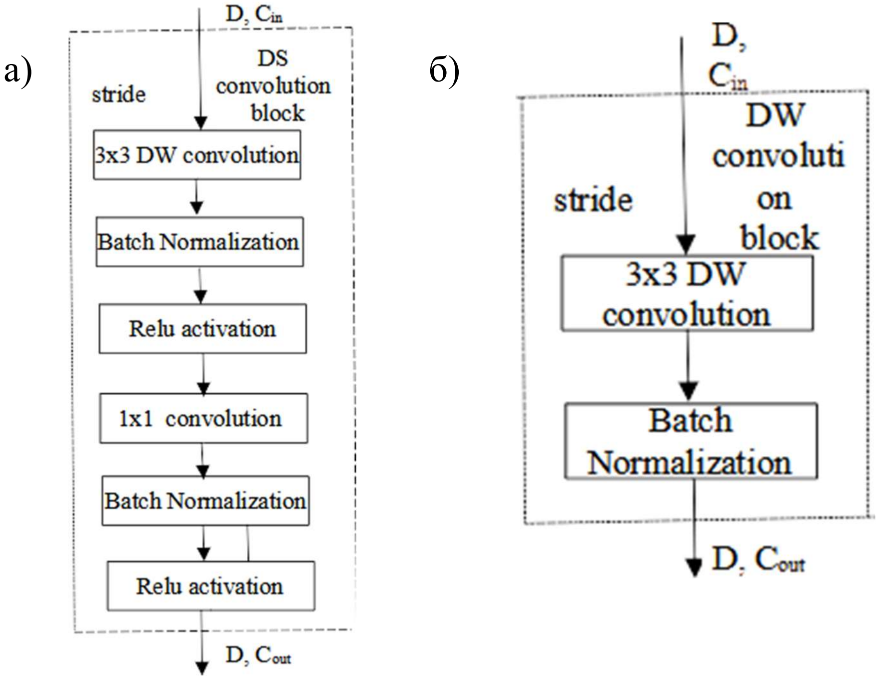


Figure 3.19. Convolutional blocks: a) deep shared convolution block (DS); b) deep convolution block (DW); D – image dimension, C_{in}, C_{out} — number of input and output channels, stride — convolution step

MobileNet architecture is based on the use of deep shared convolution (DSW - depthwise separable convolution), which divides the standard convolution into two parts: deep convolution (DW - depthwise convolution) and 1×1 point convolution (pointwise convolution). Unlike standard convolution, which simultaneously processes and combines input data into a new set of output data in one pass, this method separates these operations to improve efficiency. Deep shared convolution is performed in two stages. At the first stage, each input channel is processed by a separate filter using deep convolution. In the second stage, the output from the deep convolution is combined using a point convolution. This allows to split a standard convolution into two layers: one for filtering and the other for combining. This approach significantly reduces the computational load and the size of the model [124].

The network architecture includes two types of blocks shown in Figure 3.19. The first type implements deep shared convolution (DSW) using batch normalization and ReLU activation. The second type is a deep convolution with batch normalization and the same activation function. Basically, these blocks use convolution with step 1 (stride = 1), while convolution with step 2 (stride = 2) It is used to reduce the spatial dimension. Two main types of convolutional levels are formed from convolutional blocks. The structure of the blocks of the first and second types is shown in Figures 3.20 and 3.21. The feature of the base block of the first type is the use of a residual connection. According to this principle, the result of applying successive DS and DW type convolutions is summed up with the result of a separate deep convolution.

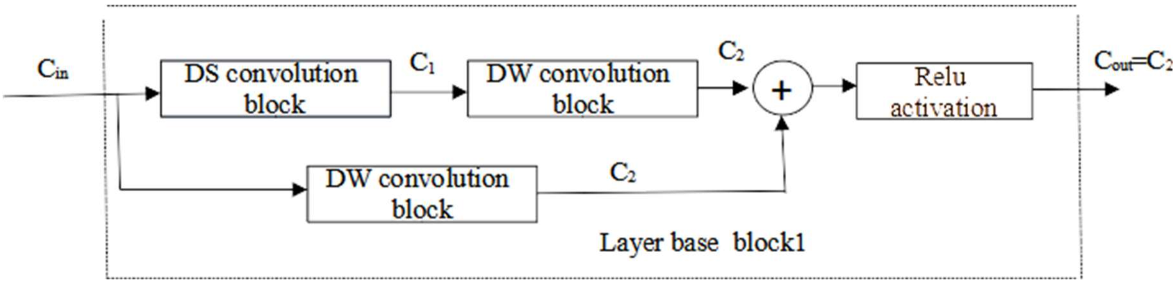


Figure 3.20. The structure of the base block of the first type of convolutional level. C_{in} and C_{out} denote the number of input and output channels, and C_1 and C_2 represent the number of channels in the deep split convolution and deep convolution, respectively

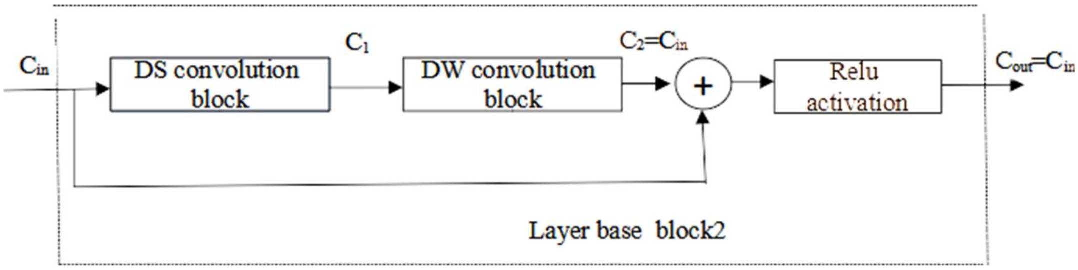


Figure 3.21. The structure of the base block of the second type of convolutional level. C_{in} and C_{out} denote the number of input and output channels, and C_1 and C_2 represent the number of channels in the deep split convolution and deep convolution, respectively

Each convolutional layer in the network is created by combining these basic blocks. In Figure 3.22 the structure of the convolutional network layer is presented, which includes a base block of the first type and N base blocks of the second type.

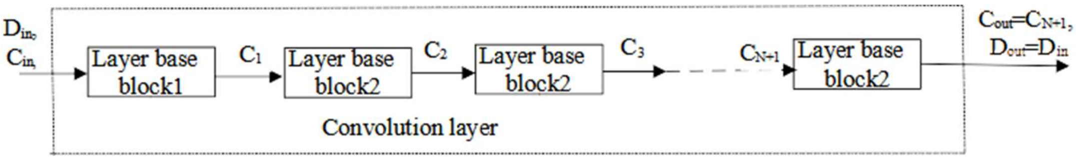


Figure 3.22. Convolutional network layer. D_{in} and D_{out} denote the dimensions of the input and output feature maps, and C_{in} and C_{out} represent the input and output number of channels. C_1 denotes the number of channels in the base block of the first type, and C_2, ... C_{N+1} - the number of channels in the corresponding blocks of the second type

The initial part of the encoding network begins with a conventional convolutional layer using a 3x3 core and a convolution step of 2, followed by the application of batch normalization and the maximum pooling operation. This is followed by several convolutional layers, where each layer is represented by a sequence of basic blocks of the convolutional level, as shown in Figure 3.22. Each subsequent layer increases the number of filters and reduces the spatial dimensions of feature maps.

In this paper, it is proposed to use an encoder consisting of 4 convolutional layers. The parameters of these convolutional layers are shown in Table 3.1. The encoder works with input images with a dimension of 512x512 and is a modification of the Mobile Net network for mobile devices in terms of the number of layers and their parameters. This modification allows to work with larger parts of the images, which allows for more detailed segmentation of large satellite images.

Table 3.1. Parameters of convolutional layers in the encoder

Layer number	The dimension of the Din input	The dimension of the output Dout	Number of input channels Cin	Number of Cout output channels	Number of Type 1 blocks	Number of Type 2 blocks
1	512	128	3	64	-	-
2	128	128	64	256	1	2
3	128	64	256	512	1	3
4	64	32	512	1024	1	5

The decoding part of the network consists of several levels, where each level begins with increasing the dimension of the input feature map and combining this result with the feature map obtained from the previous encoder level. The combined result is then subjected to deep convolutions using batch normalization and the Relu activation function. Figure 3.23 shows the structure of the decoding layer of the network used in this work.

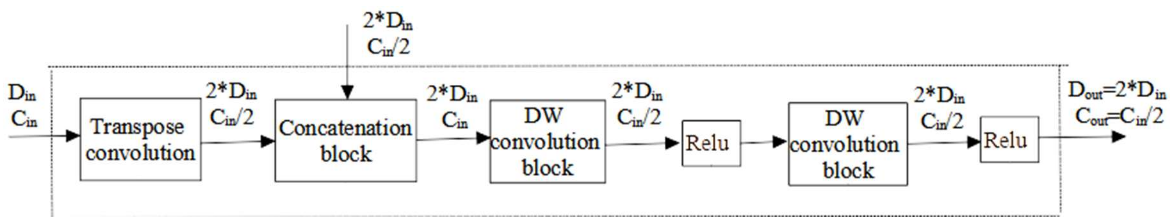


Figure 3.23. The structure of the decoding layer. D_{in}, D_{out} — dimensions of input and output feature maps; C_{in}, C_{out} – input and output number of channels

To increase the dimension of the input feature map, a transposition convolution is used, which doubles the dimension, but reduces the number of channels by half. These changes help to align the dimension and number of channels with the feature map coming from the previous layer of the encoder. After combining these maps, a new feature map is created, the size of which corresponds to the dimension of the corresponding encoder layer, and the number of channels is equal to the number of input channels. This resulting feature map is processed using two deep convolution blocks. The output of the decoding layer is a feature map that is transmitted to the next decoding layer. In the last decoding layer, the input data is the feature map of the penultimate decoder layer and the original image. This layer includes an additional deep convolution, the number of channels in which corresponds to the number of classes that need to be recognized in the image. The sigmoid function is used for activation. The output of this layer is a "heat map" that visualizes a segmented image.

The use of deep convolutions in the encoding and decoding parts of the proposed network significantly reduces the number of parameters configured during network training and then used during its operation, which reduces the requirements for computing resources and increases its performance.

The procedure for training the proposed network and the results of its use are described in the chapter 4.

3.6. Methodology for determining agricultural land

Land use maps or land cover maps are the main tool for managing information about the earth's surface and the interaction between different types of land cover. In Uzbekistan, until the 1990s, most of the information on land use came from the National Cartographic and Geodetic Program. Land-use maps are used not only for land management, but are also important for environmental purposes such as land use, land-use change and forestry, in climate change policy and biodiversity research.

The main purpose of this study is to test the possibility of using satellite sensor data to accurately and accurately map the main types of irrigated crops using deep learning algorithms. To achieve this goal, it is necessary:

- Map and compare the performance of deep learning algorithms such as Unet and VG19 for major irrigated arable lands by crop type with Google Earth and Sentinel data of medium and high resolution;

- test various combinations of vegetation indices, such as DV, AVI and AVI, as input data to obtain a classification of crop types;
- compare the areas of all received agricultural land use maps with the OSS data of the State Statistics Committee of the Republic of Uzbekistan.

This study focuses on some cities and the Tashkent region in the Central Asian country of Uzbekistan. Agricultural land accounts for about 62 percent of the total area of the country, most of which is pasture. Cultivated lands occupy only 10 percent of the total area of the country, which is about 425 square kilometers [112]. The region borders Kazakhstan in the north and northwest, Kyrgyzstan in the northeast, Namangan region in the east, Tajikistan in the south and Syrdarya region in the southwest. Given that arable land is mainly distributed in the low-lying areas of this region, the analysis was limited to these areas (Figure 3.24).

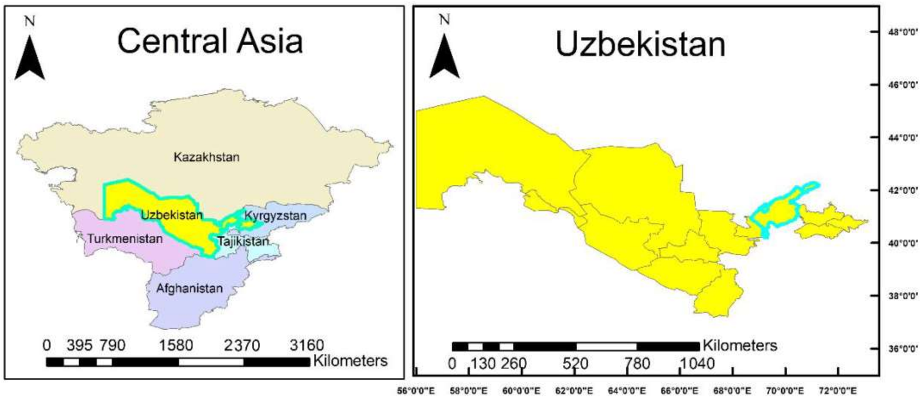


Figure 3.24. Geographical location of the research region

The climate is characterized by a typical continental regime, with cool and humid winters, as well as hot, dry and long summers; average temperatures range from -1°C to -2°C in January and reach 26.8°C in July. The total rainfall during the year is approximately 300 mm in the plains, 300 to 400 mm in the foothills and 500 to 600 mm in mountainous areas. The main precipitation comes in early spring, and in alpine areas it falls in the form of snow. The Syrdarya River and its tributaries, Chirchik and Akhangaran, are mainly fed by melting snow and glaciers, and are used for irrigation and hydroelectric power generation. Approximately 40 percent of irrigated land in Uzbekistan is used for wheat cultivation, 36 percent is occupied by cotton crops, and the remaining

24 percent is allocated to other crops such as fruits, vegetables, cattle breeding and various types of cereals. In the Tashkent region, the share of acreage under cotton and wheat is more than 61 percent of the total in 2018.

The S2 and L8 data (Sentinel 2 and Landsat 8) covering the relevant study region are multispectral images necessary for calculating vegetation indices. (Algorithms for calculating vegetation indices are described in Section 2.3.) This data was downloaded from the Google Earth Engine website for several dates of the vegetation growth period from May to October 2018. In addition, only images without clouds are available during this period. The specification of spectral bands for the two sensor systems used in the analysis can be seen in Figure 3.25 [114].

Band Number	S2 MSI			L8 OLI		
	Description	Wave-Lengths (nm)	Spatial Resolution (m)	Description	Wave-Lengths (nm)	Spatial Resolution (m)
1	Coastal aerosol	433Œ453	60	Coastal aerosol	433Œ453	30
2	Blue	458Œ523	10	Blue	450Œ515	30
3	Green	543Œ578	10	Green	525Œ600	30
4	Red	650Œ680	10	Red	630Œ680	30
5	Vegetation Red Edge 1	698Œ713	20	NIR	845Œ885	30
6	Vegetation Red Edge 2	733Œ748	20	SWIR 1	1570Œ1650	30
7	Vegetation Red Edge 3	773Œ793	20	SWIR 2	2100Œ2300	30
8	Near-Infrared (NIR)	785Œ900	10	Panchromatic	500Œ680	15
8a	Narrow NIR	855Œ875	20			
9	Water vapor	935Œ955	60	Cirrus	1360Œ1390	30
10	SWIR-Cirrus	1360Œ1390	60	Thermal Infrared (TIRS) 1	10,600Œ11,200	100
11	SWIR 1	1565Œ1655	20	Thermal Infrared (TIRS) 2	11,500Œ12,500	100
12	SWIR 2	2100Œ2280	20			

Figure 3.25. Spectral band specifications for S2 and L8

After uploading the S2 image, SWIR 1 and SWIR 2 channels were resampled to a resolution of 10 m. The L8 and S2 data were then adjusted to take into account the atmosphere from upper atmosphere reflectivity (TOA) to surface reflectivity. This was done using the Sen2Core package Sentinel Hub. Then all the S2 and L8 tiles are combined for each month separately and displayed in the study area. The data transformed in this way is used to calculate the NDVI, SAVI, NDVI and SAVI indices. As a result, the monthly time profiles NDVI, SAVI, NDVI and EVI were obtained, which are the initial data for the ML classifiers.

3.7. Neural network for classifying crops

Convolutional neural networks (CNNs) are widely used to identify crops, as they effectively cope with the classification of images of various types. In this context, several CNN variants can be distinguished and their characteristics can be considered when applied to the classification of agricultural crops [115]:

1. LeNet-5:
   - This is one of the first convolutional neural networks developed by Jan LeCun.
   - Consists of several layers of convolution and pudding, as well as fully connected layers at the end.
   - Usually used for classification tasks with a small number of classes.
2. AlexNet:
   - Developed in 2012 and has become a pioneer in the field of deep learning and CNN.
   - Contains several layers of convolution and pooling, as well as normalization and dropout layers to prevent overfitting.
   - Widely used for image classification, including agricultural crops.
3. VGG (Visual Geometry Group) Net:
   - Has a very deep architecture using small 3x3 bundles.
   - Simple and efficient architecture, easily adaptable to various classification tasks.
   - Used to classify images in various fields, including agriculture.
4. ResNet (Residual Neural Network):
   - Introduces the concept of "residual blocks", which allows to train deep neural networks without the problem of gradient attenuation.
   - Shows high efficiency in image classification and can be successfully applied to agricultural data.
5. Inception (GoogLeNet):

- Has a modular design using parallel bundles of different sizes.
- Allows efficient use of resources and improves the quality of classification.
- Used to classify images of agricultural land and crops.

In this project, the VGG neural network was used to classify agricultural products.

VGG (Visual Geometry Group) Net is a convolutional neural network developed by researchers from the Visual Geometry Group at the University of Oxford. This neural network has been widely recognized for its simplicity and high performance in image classification tasks. The VG 19 model (also known as G Net-19) has the same basic idea as the VG 16 model, except that it supports 19 layers. The numbers "16" and "19" refer to the weight layers of the model (convolutional layers). Compared to VG 16, VG 19 contains three additional convolutional layers. When building a VGG network, very small convolutional filters are used. Thirteen convolutional layers and three fully connected layers make up VGG.

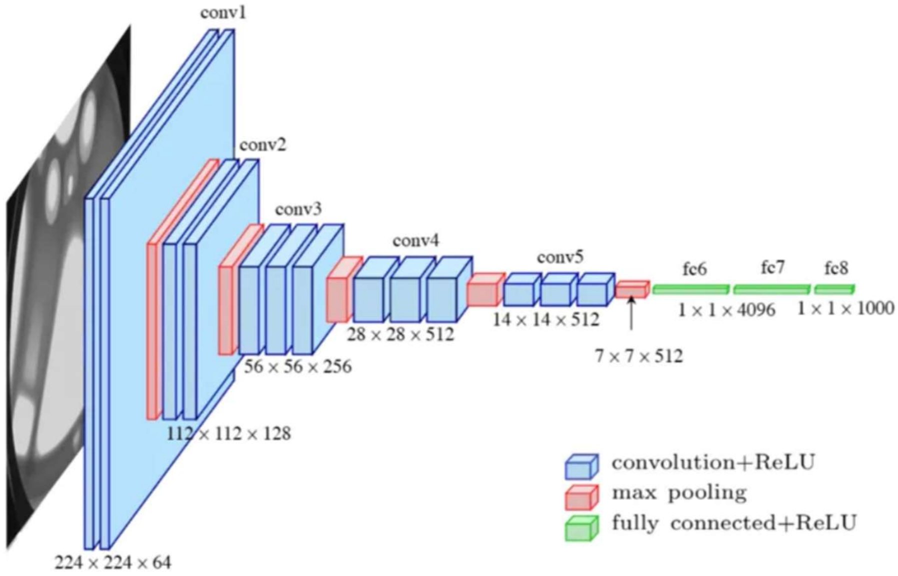


Figure 3.26. VGG-Net architecture

Consider the VGG architecture:

- Input data: VGGNet accepts 224x224 pixel images as input. To maintain a constant size of ImageNet input data.

- Convolutional layers: Convolutional layers in VGGNet are represented by sequentially arranged convolutional operations using 3x3 filters and the ReLU activation function. Every two convolutional layers are followed by MaxPooling layers.
- Fully connected layers: A series of convolutional and puddling layers are followed by fully connected layers for classification. At the end of a neural network there is usually a fully connected layer with a softmax activation function to predict the probabilities of belonging to different classes.

The VGGNet architecture is easy to understand and implement, which makes it easier to use and modify. In general, the VGG neural network differs from other neural networks in its deep architecture, the use of small convolutional filters, a simple and uniform structure, as well as high performance on various image classification tasks.

In this paper, a modification of the architecture of the VGG network used is proposed to reduce computational costs. The modification consists in replacing conventional convolutions with deep convolutions in all convolutional layers of the network. This modification allows to significantly reduce the number of parameters configured during network training and then used during its operation, which reduces the requirements for the computing resources used and increases its performance.

In this project, to train such a modified network, a dataset was used in which 160 images with a size of 224x224 pixels corresponded to each class of crops. The procedure for training the proposed network and the results of its use are described in the chapter 4.

3.8. Methodology for detecting active urban territory

The discovery of an active urban area is the process of identifying and analyzing areas of the urban environment that are actively used by people or are subject to significant changes in different periods of time. This includes traffic, commercial activity, pedestrian traffic, etc. This process can be performed as follows:

1. Data preparation:

- Creating a collection of images containing various urban environments: about 13,000 images were used in the project.
- Markup of images according to the recognized classes of objects. This is usually done manually by tracing the boundaries of the objects. The project uses already marked-up images. The total number of object classes is 21 classes.

2. Choosing the model architecture for image segmentation. The project proposes to use an architecture based on U-Net and MobileNet networks.
3. Preparation of the training data set:
    - Separation of images and their labels into sets of training and test data: images are divided into fragments and distributed into folders Train, Test and Validation.
    - Images and their characteristics are converted into a format suitable for training the model, for example, the format accepted by the neural network.
4. Model Training:
    - The selected model must be trained on a set of training data. During training, the model adjusts its parameters to accurately predict the types of fields in the images.
    - Selectable loss function and parameter search optimization method are usually used to train the model. The project uses cross-entropy as a loss function, and the Adam optimization algorithm is used for optimization.
5. Evaluation of the model:
    - Calculation of achieved segmentation quality parameters and visualization of segmentation results, as well as evaluation of model performance.
6. Application of the model:
    - Application of a trained model for segmentation of new images of the urban environment.
    - Using the segmentation results for further analysis, for example, for mapping urban areas, analyzing urban infrastructure planning, etc.

Semantic segmentation using neural networks is widely used in the detection of active urban areas, since it allows to accurately identify various classes of objects in the image, including active and inactive cities. Therefore, in this project, the segmentation process was implemented based on the neural network architecture. The results obtained using the neural network are presented in chapter 4.

3.9. Evaluating the quality of results

Quality assessment is the process of evaluating the results of applying a model or algorithm by comparing its output results with true values (the gold standard). This is an important stage in the development and evaluation of any machine learning model or algorithm, as it allows to understand how well the model is able to make predictions and how it generalizes to new data.

Key metrics used to assess the quality of machine learning models [116]:

1. Accuracy measures the proportion of correct model predictions relative to the total number of predictions. Formally, this is the number of correct predictions divided by the total number of predictions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (3.1)$$

   where TP (True Positive) - is the number of true positive predictions, TN (True Negative) - is the number of true negative predictions, FP (False Positive) - is the number of false positive predictions and FN (False Negative) - is the number of false negative predictions.

2. Accuracy of classification (Precision):

   This is a metric used in classification tasks that measures the proportion of correct model predictions relative to the total number of examples. It's just a fraction of correctly classified examples.

$$precision = \frac{TP}{TP + FN} \qquad (3.2)$$

3. Completeness (Recall):

   The proportion of correctly recognized objects of the main class among all objects of the main class from the sample. Completeness - the probability of correct classification when an image belongs to a given class.

$$recall = \frac{TP}{TP + FN} \qquad (3.3)$$

4. Sensitivity – the probability of giving the correct answer for the images of the main class.

$$sensitivity = \frac{TP}{FP + TN} \qquad (3.4)$$

5. Error Matrix: The error Matrix is a table where the rows represent the actual classes and the columns represent the predicted classes. This allows to better understand what types of errors the model makes: false positive (FP), false negative (FN), etc.

Accurate assessment of the quality of the model is crucial for successful deep learning. Several methods are used to assess the quality of the CNN model:

1. The matrix of confusion. This is a table that allows to visualize the quality of the classification model by comparing the actual and predicted classes for a dataset. It is the basis for calculating various classification quality metrics. The confusion matrix is usually a square matrix where the rows represent the actual classes and the columns represent the predicted classes. Consider an example of a confusion matrix for binary classification:

The actual class	Negative	Positive
Negative	TN	FP
Positive	FN	TP

Table 3.2. Confusion matrices for binary classification problems

where:

- TN (True Negative): the number of correctly predicted negative examples.
- FP (False Positive): the number of false positive predictions (negative examples, but predicted as positive).
- FN (False Negative): the number of false negative predictions (positive examples, but predicted as negative).
- TP (True Positive): the number of correctly predicted positive examples.

The confusion matrix allows to analyze the quality of the model, identify the types of errors that it makes, and calculate various quality metrics such as accuracy, completeness, F1-measure, etc., based on the values contained in the matrix.

2. Cross-Validation is a method of evaluating the quality of a machine learning model, which allows to more reliably assess the generalizing ability of the model on new data. The basic idea of cross-validation is to divide the available data into several parts (called "folds" or "folds"), train the model on one part and test it on the remaining parts. There are several different approaches to cross-validation, but one of the most common is K-fold Cross-Validation, which includes the following steps:
   1. Data separation:
      - The original data set is divided into K equal parts (folds).
   2. Training and evaluation iterations:

- For each iteration, one of the funds is used as a test dataset, and the remaining K-1 funds are used as a training dataset.
- The model is trained on a training set and evaluated on a test set.

3. Averaging metrics:
   - The evaluation results (for example, the values of quality metrics) are averaged over all K iterations to obtain an overall estimate of the model's performance.

Advantages of cross-validation:

- Allows to better evaluate the generalizing ability of the model, since each data sample is used in both training and testing.
- Reduces the likelihood of overfitting the model on a specific data set.
- Provides a more stable assessment of the model's performance, since the assessment is carried out on several different data partitions.

4. Evaluation of a test dataset is the process of evaluating the quality of a machine learning model on deferred data that the model did not see during training. This is an important step in the development of models, as it allows to evaluate the ability of the model to generalize to new, previously unknown data.

Accuracy estimation in the UNet architecture, as in any other neural network architecture, can be performed using various metrics, depending on the type of task, data set, and model requirements. Typical metrics that can be used to evaluate the accuracy of the U-Net model [117]:

1. Dice Similarity Coefficient):
   - This is a metric that measures the degree of similarity between two areas. In the case of image segmentation, the Dice index is used to assess the similarity between true and predicted masks.
   - Formula for calculation:

$$Dice = \frac{2 \times |A \cap B|}{|A| + |B|} \qquad (3.5)$$

where A is the true mask, B is the predicted mask, |·| denotes the cardinality of the set.

2. Intersection over Union (Itu):
   - This is another metric for measuring the degree of overlap between the true and predicted masks.
   - Formula for calculation:

$$IoU = \frac{|A \cap B|}{|A \cup B|} \quad (3.6)$$

3. Accuracy:
   - In the context of image segmentation, accuracy measures the proportion of pixels that have been correctly classified.
   - Formally, it is the ratio of the number of correctly classified pixels to the total number of pixels in the image.
4. Average accuracy (Mean Accuracy):
   - This is the average accuracy value for all classes.
5. Mean Error:
   - This is a metric that measures the average distance between the true and predicted masks.
6. The average distance to the contour (Mean Distance to Boundary):
   - This is a metric that measures the average distance from pixels in the predicted mask to the nearest pixel in the true mask.
7. The Jaccard Index, also known as the intersection coefficient or the Jacquard similarity measure, is a metric used to assess the similarity between two datasets. In the context of image segmentation, it is used to measure the degree of overlap (in area) between the true and predicted masks. The formula for calculating the Jaccard Index looks like this and coincides with the calculation of the IoU metric:

$$J(A,B) = \frac{|A \cap B|}{|A \bigcup B|} \quad (3.7)$$

where:

- A is the set of pixels in the true mask,
- B is the set of pixels in the predicted mask,
- |·| denotes the cardinality of the set.

The Jacquard index is in the range from 0 to 1, where 0 indicates the complete absence of intersection between the masks, and 1 indicates their complete coincidence.

These metrics are commonly used in computer vision tasks to evaluate the effectiveness of classification or segmentation models such as CNN. Accurate assessment of model quality is crucial for successful deep learning, and various accuracy assessment methods should be used to reliably assess model quality. The use of evaluation metrics in the loss function (Jacquard index, IoU, etc.) helps to optimize model training in neural networks correctly.

Conclusion to Chapter 3

1. It is proposed to receive data for this project from the Sentinel Hub and Google Earth platforms. Because two platforms are open for use and allow to upload high-quality images. The primary correction of the atmosphere can be performed based on additional settings on the platforms, if this is not possible, the correction of the atmosphere should be performed using a method based on neural networks.
2. It should be noted that the encoder-decoder architecture is becoming increasingly popular in semantic segmentation due to its high flexibility and performance. Therefore, this project uses U-Net and MobileNet with encoder-decoder architecture in the process of atmospheric correction, segmentation of urban and agricultural lands. The standard encoder-decoder architecture was used for atmospheric correction, and the basic U-Net architecture was used to track urban and agricultural sites, detect objects, and monitor urban changes. To achieve better results, this was achieved by modifying the U-Net architecture, that is, the coding part of the U-Net architecture was replaced by the coding part of the MobileNet architecture. Thus, the result is improved, and all the results are presented in 4 chapters.
3. The process of semantic segmentation was implemented to classify and identify agricultural products. The classification process is based on a neural network and implemented using the VGG 19 architecture. Before training the neural network, the images were segmented by index VI. After analyzing the NDVI, SAVI and EVI indices, the data obtained were trained using the VGG 19 neural network architecture.
4. For segmentation and classification of areas and objects, it is proposed to use neural networks with U-Net, MobileNet and VGG architectures. All these based architectures were chosen based on speed, quality of results, simplicity and, most importantly, reducing the load on computing resources.

CHAPTER 4. IMPLEMENTATION AND EXPERIMENTAL STUDY OF TERRITORY MONITORING METHODS BASED ON SATELLITE IMAGES

Satellite image-based territory monitoring involves the use of satellite images to monitor the current state of the territory, as well as to track changes in a specific geographical location over time. In this project, the possibilities of monitoring rural and urban areas based on segmentation and processing of satellite data are experimentally analyzed. The experimental analysis consists of:

1. Neural networks were used for atmospheric correction of satellite images.
2. New methods of monitoring agricultural land and identification of agricultural products were used.
3. The result was obtained based on the integration of neural networks into urban monitoring and object detection.

This chapter presents the results of the above methods.

4.1. Territory monitoring tool

4.1.1. Atmospheric correction based on a neural network

The most suitable network architecture for such conversion is the encoder–decoder architecture. The structure of the proposed neural network is shown in Chapter 3 (Figure 3.15). The encoder has only three encoding levels. In fact, the encoder is an ordinary convolutional network trained to classify the input image. The decoder has the same number of layers and performs the function of interpolating the encoder output. The decoding layer (Figure 3.15) is a reverse convolution followed by batch normalization.

A dataset for training and testing a neural network is formed on the basis of available satellite images of L1C and L2A levels for several regions of the earth's surface obtained at different times of the year. In this case, data from spectral channels B04 (R), B03 (G), B02 (B) of the visible range and data from channel B08 (NIR) of the near infrared ranges are used. The data from these channels is preprocessed and converted into four-channel images. The structure of the preprocessing algorithm is described in Chapter 3 (Figure 3.16). First, the channel images are reduced to the same dimension, then they are divided into 64 parts, normalized in brightness and form 64 four-channel images. The set of images obtained in this way is randomly divided into training, validation and test samples containing 80%, 10% and 10% of the dataset volume, respectively.

When forming the dataset, 355 L1C level images and the same number of corresponding L2A level images were used, each with a dimension of about 2048x2048 pixels. Thus, the network was trained and tested on a set of 22,720 four-channel images of the L1C level with a dimension of 128x128 pixels, and the corresponding images of the L2A level were the target ones. The set of original multispectral images is downloaded from Sentinel Hub and contains data for several regions of Uzbekistan for 3 years.

When training the network, the RMS error MSE was used as a loss function. This standard error is an estimate of the accuracy of atmospheric correction. The Adam optimization algorithm was used to search for network parameters.

The results of network training on the used dataset are shown in Figure 4.1. At the same time, it was possible to achieve a correction accuracy of about 99.5%. In Figure 4.2 an example of visualization of correction results using a neural network is shown.

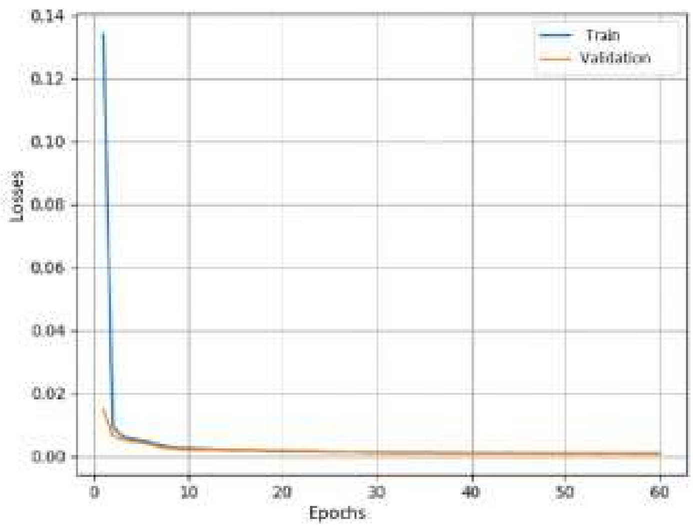


Figure 4.1. Dependence of losses (mean square error) on the training epoch

a) b)

Figure 4.2. Images of levels 1C and 2A: (a) Image without atmospheric correction — level L1C (b) Atmospheric correction using a neural network

During atmospheric correction, in addition to a three-channel RGB image reflecting the corrected visible part of the spectrum, a single-channel NIR image representing the corrected near-infrared range of the spectrum is also formed. These images are necessary, among other things, for calculating vegetation indices.

During the research, satellite images were also processed not only from Sentinel, but also from other satellites. The results showed acceptable correction accuracy for these "third-party" neural network images.

4.2. Neural networks for semantic segmentation of satellite images

Semantic segmentation of satellite images using neural networks involves assigning each pixel of an image a label indicating the class of objects to which it belongs. This includes mapping vegetation cover, monitoring urban changes, and crop analysis.

In this paper, the proposed MobileNet-Unet network architecture, described in section 3.5, was studied for semantic segmentation. The results of its work were compared with the results of the network with the Unet architecture, which is usually used in semantic segmentation tasks. In order for such a comparison to be adequate, the training of both networks was carried out on the same dataset.

4.2.1. Dataset and preprocessing

To train the networks, a pre-prepared LandCover dataset [118] was used, supplemented with images related to the regions of Central Asia. However, these additional images were without atmospheric correction. Therefore, atmospheric correction was carried out for them using the network proposed in this work. In total, the set contains 1,146 high-resolution satellite images of areas of the Earth's surface. In addition to the images themselves, it includes masks that display the type of earth's surface for each pixel of the corresponding image. The following types are present in the dataset: agricultural land, pastures, barren lands, buildings and structures, woodlands, and water bodies. Other surface types that are not included in this list are displayed as an unknown type.

High-resolution satellite images are too large to be processed directly on a neural network. Simply zooming out of the original images will result in loss of segmentation accuracy. Therefore, the first stage of preprocessing is to separate the images of the dataset and their corresponding masks into fragments. When designing the network, the dimension of the input images 512x512 pixels was chosen, which allows, on the one hand, to reduce the computational costs of training and using the network, and on the other hand, will ensure sufficient segmentation accuracy. The resulting fragments of images and masks are scaled to the specified dimension. In this work, each original image is divided into 16 fragments.

In Figure 4.3 shows the algorithm for preprocessing images included in the original dataset. The dataset consists of RGB satellite images of certain territories and their corresponding masks. Each mask is an RGB image with a specified number of colors. At the same time, each type of earth's surface is displayed in the mask with its pre-determined color contained in the table of colors used. Thus, the number of colors N in the mask corresponds to the number of types of the earth's surface.

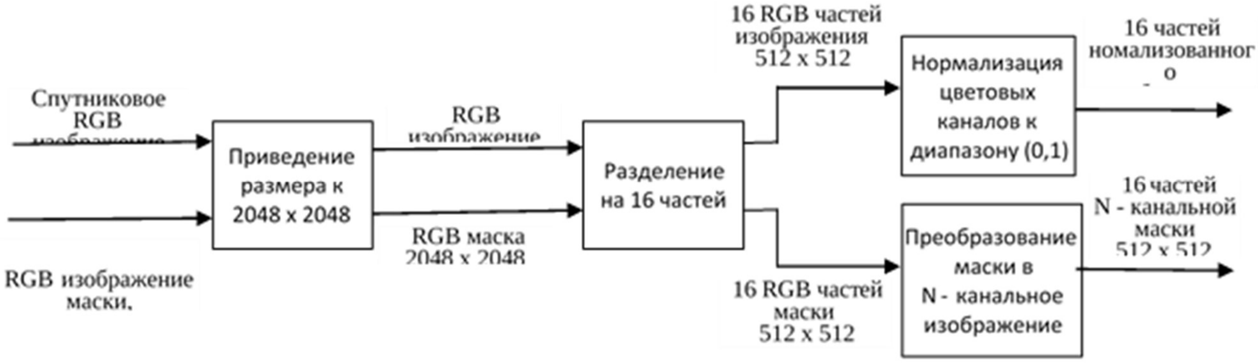


Figure 4.3. Dataset image preprocessing algorithm

All images from the original dataset are preprocessed according to the procedure described above. As a result, a working data set is formed, consisting of 18336 image fragments and their corresponding masks. The resulting working set is randomly divided into training, validation and test datasets, which make up 60%, 20% and 20% of the volume of the working set.

4.2.2. Network Training

As already noted, training and testing were conducted for two neural network architectures – the U-Net architecture and the MobileNet-Unet architecture proposed in this paper. The same parameters were used to train both networks.

A function based on the Dice coefficient was used as a loss function [119]. This coefficient is a metric of the similarity of two sets and is calculated as follows:

$$dsc = 2 * (|x \cap y|)/(|x| + |y|) \qquad (4.1)$$

where x is the predicted pixel class, and y is the true class of the same pixel obtained from the corresponding mask channel, | x | and | y | are the number of elements in each set, and |xy| is the number of matching elements in the sets. Then the corresponding loss function is defined as

$$Loss\_dsc = 1 - dsc \qquad (4.2)$$

The Adam optimization algorithm is used for iterative updating of network weights in the learning process [120]. This algorithm is an extension of stochastic gradient descent. When training the network, the recommended learning rate parameter of 10-5 was used, and algorithms were also used to automatically reduce the learning rate and stop learning early if losses did not decrease over several epochs. The network was trained using batch normalization, and a packet size of 4 was experimentally selected.

Figure 4.4 shows the training schedules of the Unet network and the proposed MobileNet-Unet network over a small number of epochs. During further training on a larger number of epochs, the values of loss functions and segmentation quality indicators changed slightly. The training results show that the proposed MobileNet-Unet architecture has increased the pixel-by-pixel accuracy of segmentation by 4.4%.

A)

B)

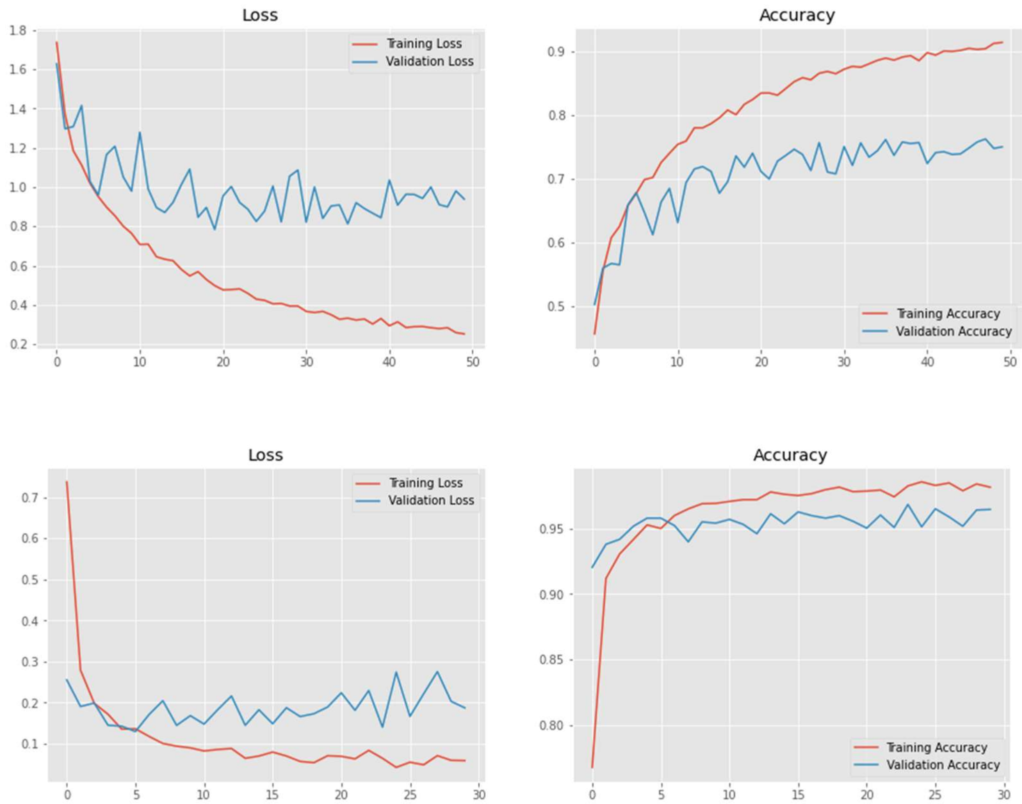


Figure 4.4. Training schedules of the Unet (A) and MobileNet-Unet (B) networks depending on the training epochs

An analysis of the architecture of the studied networks showed that about 31.4 million parameters are configured during the training of the Unet network. At the same time, the training of the proposed MobileNet-Unet network requires the configuration of 20.6 million parameters. At the same time, in the case of using conventional convolutions used in Unet, the amount of memory required for their calculation and storage of results significantly exceeds the amount of memory required when using deep convolutions in the proposed network. Thus, when using the proposed architecture, the requirements for the amount of memory required for training and operation of the neural network are significantly reduced and, therefore, simpler graphics accelerators can be used.

Network training was conducted using Nvidia graphics accelerators with different technical characteristics. Since a significantly larger amount of memory is required when training the Unet network, an Nvidia Tesla V100 video card with 40 GB of memory was used. To train the proposed network, a less powerful Nvidia GeForce RTX 3060 graphics card with 4 GB of memory was used. At the same time, the training time for both networks turned out to be approximately the same.

4.2.3. Testing

The proposed Msunet trained network was tested on a test set of images. The result of processing each of the test images is 16 parts of the segmented image. Each of these parts is a multi-channel binary image. The number of channels is equal to the number of segmented types of the earth's surface. For visualization, these multi-channel images are converted into regular RGB images using a table in which each type of surface corresponds to a specific color. Then, a full-size image is formed from 16 such images, reflecting the result of segmentation. The algorithm for visualizing segmentation results is shown in Figure 4.5. An example of segmentation of the satellite image from the test set is shown in Figure 4.6.

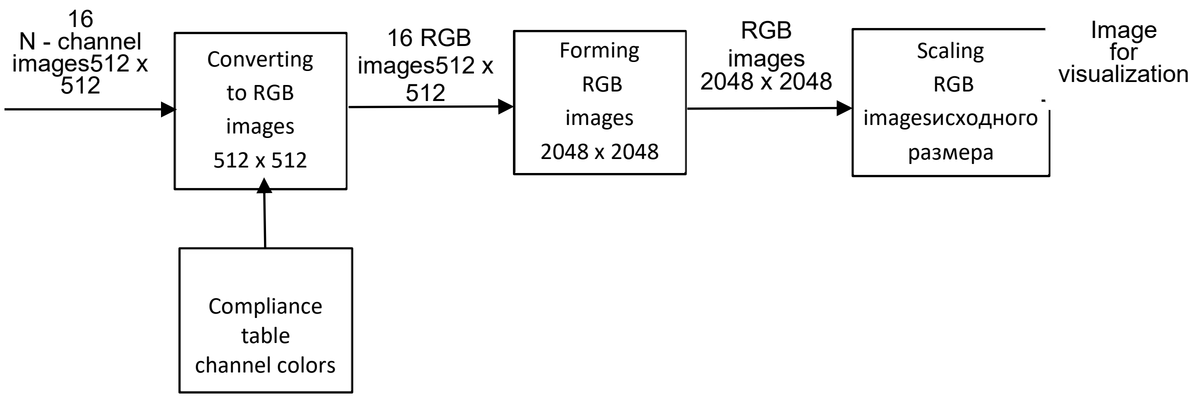


Figure 4.5. Algorithm for visualizing the result of satellite image segmentation

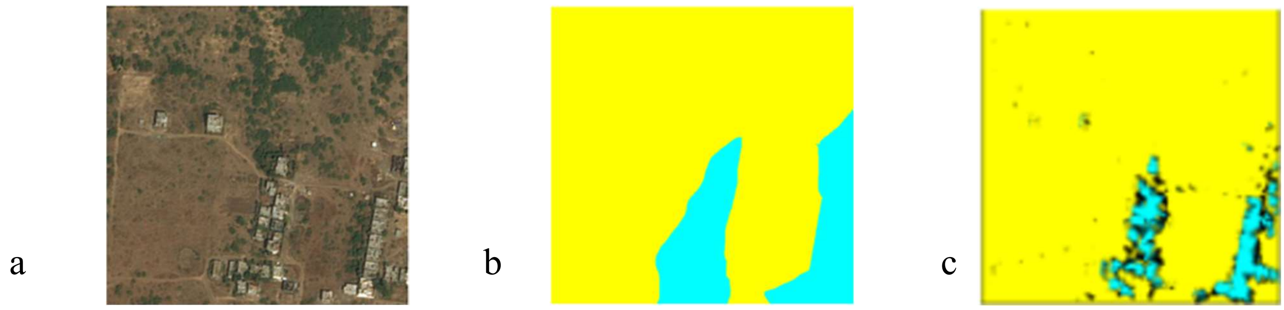
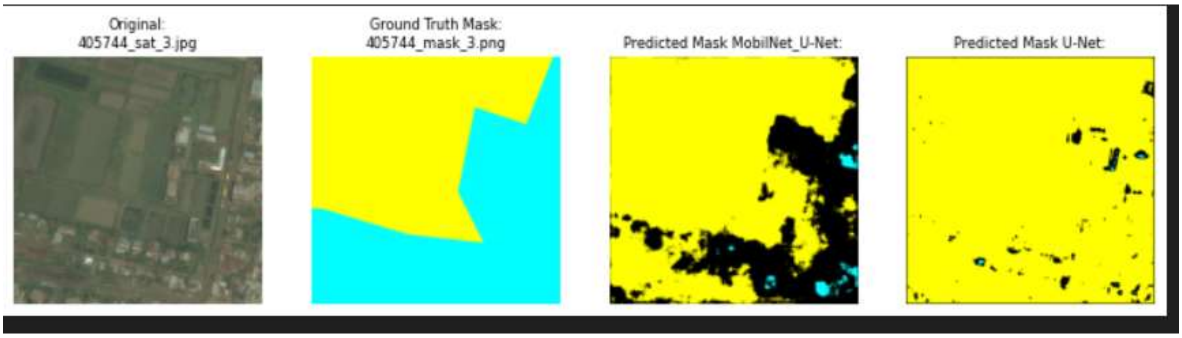


Figure 4.6. An example of segmentation of a satellite image: a) the original image; b) the marked mask; c) the result of segmentation. Color designations: yellow – agricultural land, blue — urban area, black — undefined area

During testing, the pixel-by-pixel segmentation accuracy is also determined using the appropriate marked masks from the test set. This accuracy on the test set was about 89%, which corresponds to the accuracy on the validation set used in network training. Here, the figure should be coordinated with the graphs

Figure 4.7 shows the results of segmentation of the same satellite image from the test set obtained using the proposed MobileNet-Unet network, as well as the U-Net network. Comparing these results, it can be seen that the proposed model copes much better with the segmentation of areas related to agricultural land.

a b c d



e

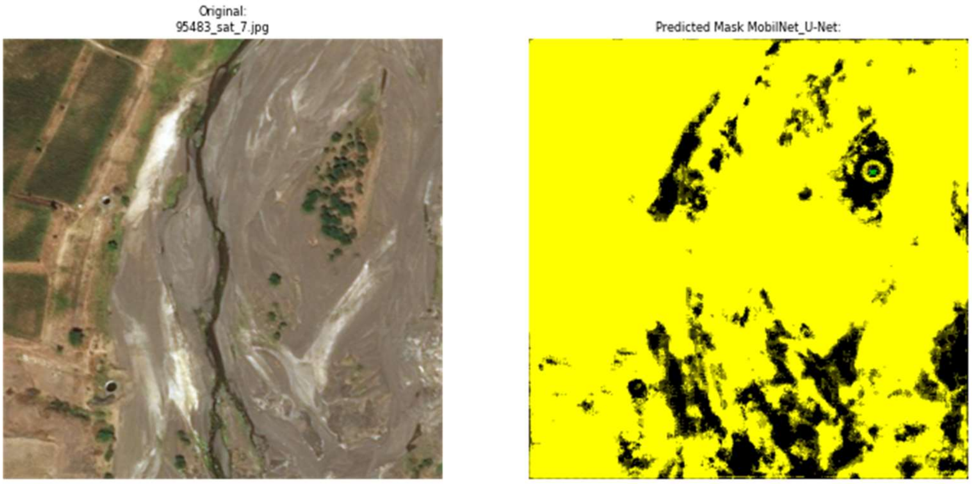


Figure 4.7. Examples of segmentation of satellite images obtained using various neural network architectures: a) the original image; b) the marked mask; c) the result of segmentation by the MobileNet-Unet network; d) the result of segmentation by the U-Net network; e) the image not included in the dataset and the result of its segmentation; Color designations: yellow – agricultural land, blue — urban area, black — undefined area

4.3. Neural network for crop classification

After the autocorrection is done, it is necessary to determine the condition of the land and agricultural products to control agricultural land. VI indices and a neural network were used to analyze agricultural territories and identify agricultural products.

In this work, the proposed VI indexes and the VGG network architecture described in sections 3.6 and 3.7 were used for semantic segmentation. The results of his work were compared with the results of networks with other architectures widely used in semantic segmentation tasks. This comparison showed good results for all neural networks, but the main requirement when choosing a network was the use of fewer computing resources.

4.3.1. Dataset and preprocessing

To train the networks, a pre-trained set of Cropland Mapping cartographic data [121] was used, filled with images related to agricultural areas and types of crops. In total, the collection contains 800 high-resolution satellite images, the collection is divided into 5 classes, each of which is represented by 160 images and consists of 4-channel images. In addition to the images themselves, it contains masks indicating the type of agricultural products for each pixel of the corresponding image. The dataset includes the following types: agricultural land, pastures, woodlands, and crop types. Other surface types not included in this list are displayed as unknown types.

Satellite images are usually of high quality and large size. At this stage, the segmentation process VI is performed before training neural networks. Therefore, at this stage, if possible, should not change the size and quality of the images. This is because all image data must be extracted using lossless indexes. After the segmentation process, all images are adapted for neural network training, i.e. the images are scaled to 224x224 pixels, since the selected VGG architecture works with this image size standard.

The dataset consists of satellite RGB images of specific areas and their corresponding masks. Each mask is an RGB image. In addition, each crop type is displayed on the mask in predefined shapes.

All images in the original dataset are preprocessed according to the procedure described above. The resulting working set is randomly divided into sets of training, verification and test data, which make up 50%, 30% and 20% of the working set.

4.3.2. Network Training

As mentioned above, the control of agricultural land and the determination of the type of crops consists of 2 stages. First, a segmentation process was carried out using the satellite image index VI. NDVI, SAVI and EVI indexes are used to analyze the quality of agricultural land and monitor agricultural areas. Ranges of a number of satellite images are used to determine the indices.

Information about indexes can be found in Section 3.6, and information about ranges can be found in Figure 3.25.

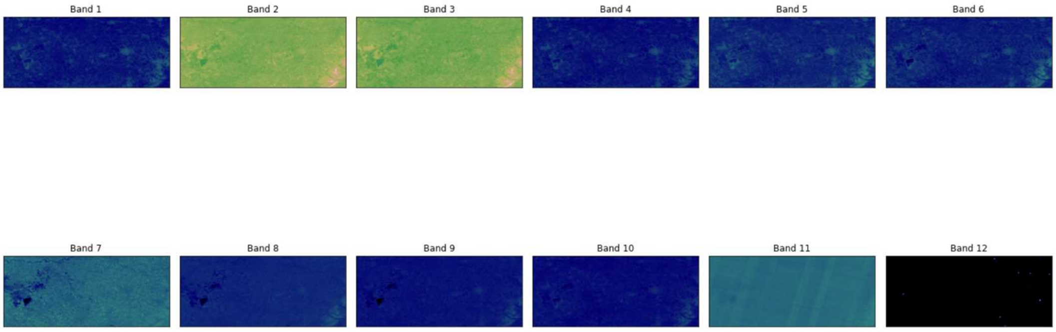


Figure 4.8. Visualization of satellite data by range

After the index segmentation process is completed, all satellite data is prepared for neural network training. The VGG neural network architecture was used, based on which the images were reduced to 224x224 pixels and a database of 160 images for each class was created.

Figure 4.9. The process of learning the classification of agricultural products

The categorical cross-entropy of the loss function was used to set up a neural network before training. Categorical cross-entropy provides a probabilistic interpretation [122]. It allows the model to output the probabilities of each class. For two discrete random variables and the cross entropy is defined as follows:

$$H(p,q) = -\sum_{x} p(x) \log q(x) \qquad (4.3)$$

This definition is not symmetrical. p is assumed to be a “true” distribution partially observed, while q is assumed to be an “unnatural” distribution derived from the constructed statistical model.

Adam's optimization algorithm is used to iteratively update the network weights during the learning process. This algorithm is an extension of stochastic gradient descent. The recommended learning rate parameter 10-3 was used to train the network. The network was trained using batch normalization, and the packet size of 16 was chosen experimentally.

Figure 4.10 shows the VGG network training schedule for a small number of cycles. In the first experiment, see a graph of 50 epochs. The training results show that the accuracy of the VGG architecture was 0.88%.

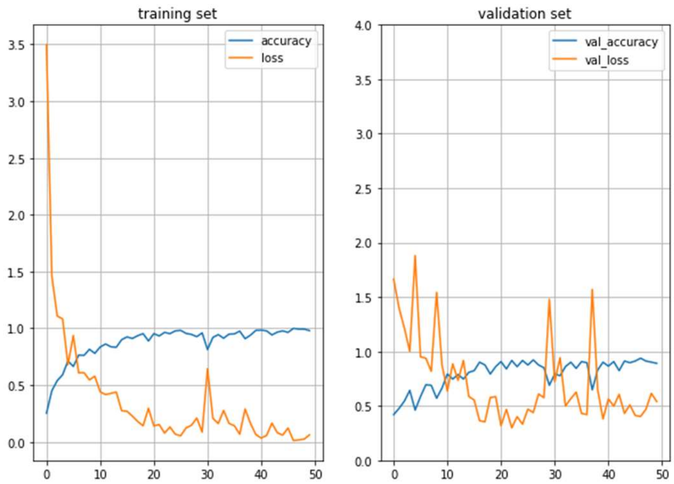


Figure 4.10. Experimental graph training based on the VGG network consisting of 50 epochs

If we experimentally retrain data based on the VGG architecture based on 100 epochs, the result will be as good as expected — 0.98%. The main reason for this result is the small size of the database. But an increase in the amount of training does not always give good results, since an increase in the amount of training can lead to retraining. Figure 4.11 shows the VGG network training schedule for 100 cycles.

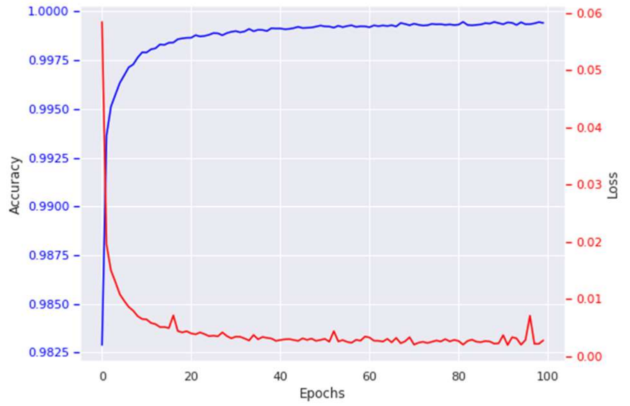


Figure 4.11. Experimental training based on the VGG network consisting of 100 epochs

An analysis of the studied network architecture showed that about 2.52 million parameters were adjusted during the training of the VGG network. In addition, when using the traditional 16 convolutions used in VG, the amount of memory required to calculate them and store the results significantly exceeds the amount of memory required when using deep convolutions in the proposed network. Thus, when using the proposed architecture, memory requirements for learning and neural network operation are significantly reduced, and therefore simpler graphics accelerators can be used.

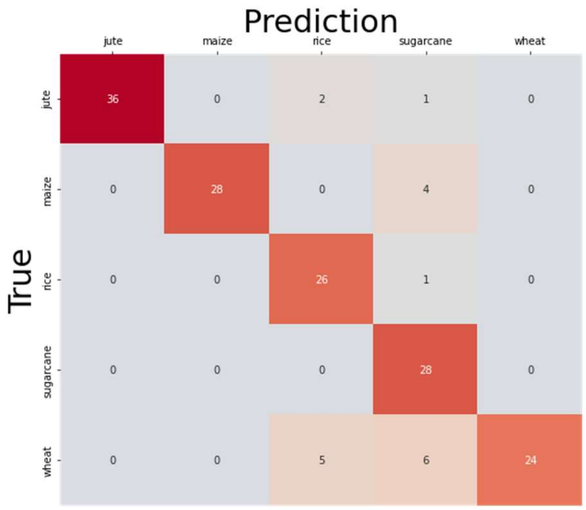


Figure 4.12. The results after learning are presented in a matrix of confusion

4.3.3. Testing

As mentioned above, the process of dividing agricultural land and products into segments was carried out in two ways. First, more than 800 datasets were used to obtain the VI results. Figure 4.13 shows an RGB image obtained from the Ferghana region.

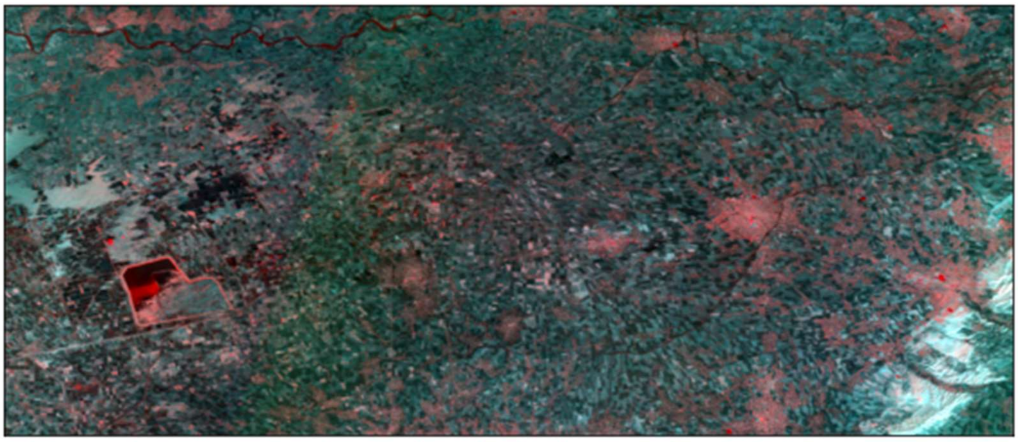


Figure 4.13. RGB composite image using stretching

In the next step, view the results of the NDVI and SAVI indexes. Information about these indices is provided in Section 2.3. It should be noted that DVI is used to determine agricultural area, and the SAVI index controls the quality of agricultural land based on analysis. Figure 4.14 shows the results of the analysis based on the NDVI index, and Figure 4.15 shows the results of the analysis based on the SAVI index.

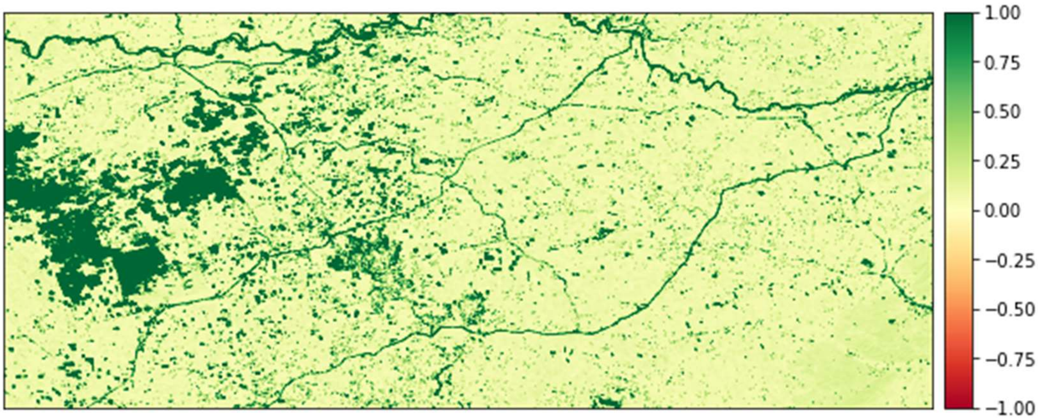


Figure 4.14. An example of segmentation of satellite images based on the NDVI index

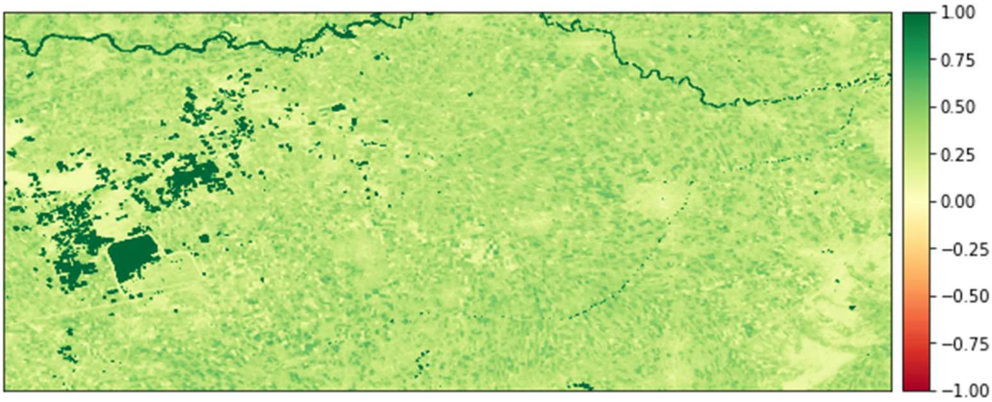


Figure 4.15. An example of segmentation of satellite images based on the SWVI index

After analyzing index VI, all data is prepared for training in a neural network. Neural network training helps to identify agricultural products. The test also determines the accuracy of segmentation using the corresponding labeled masks in the test set. This accuracy on the test set was about 88%, which is similar to the accuracy of the test set used to train the network.

Figure 4.16 shows the classification of agricultural products by index. The figure was taken from a satellite, the image quality is high, it was taken from an average distance.

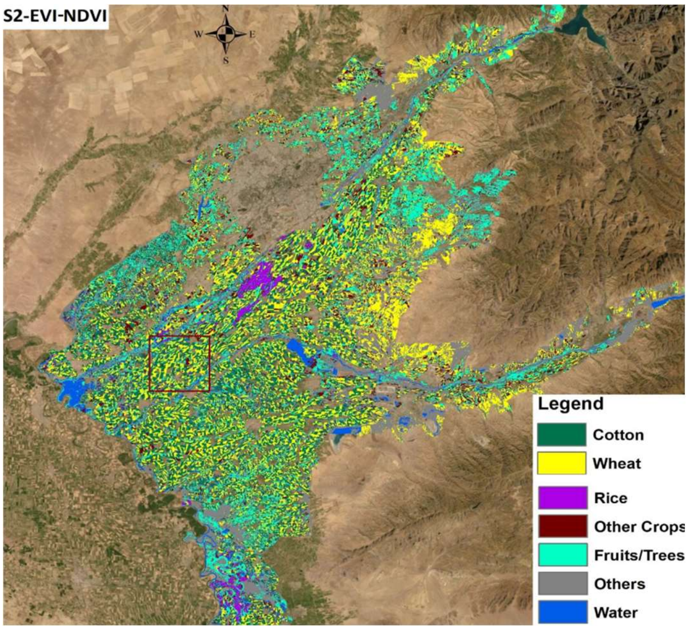


Figure 4.16. The result of the classification of agricultural products according to the EMBI and NDVI indices for the Tashkent region. The original image was obtained from the Sentinel 2 satellite

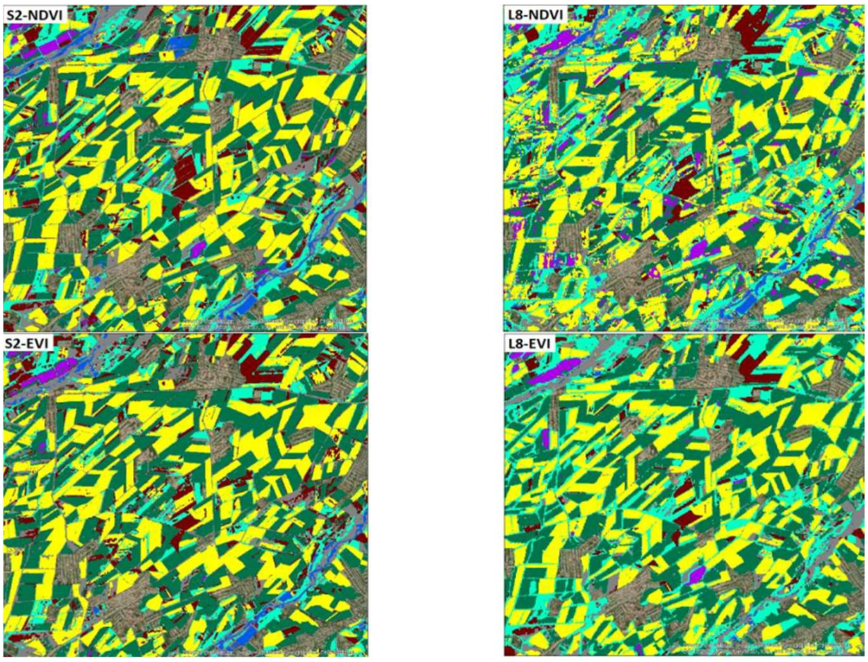


Figure 4.17. The result of the classification of agricultural products according to the EMBI and NDVI indices for a part of the Tashkent region. Color designations: yellow – wheat, blue — water, green — cotton, purple – rice, red - other crops

In Figure 4.18 shows the result of the classification of agricultural products for the entire Tashkent region, made up of processed images of its parts.

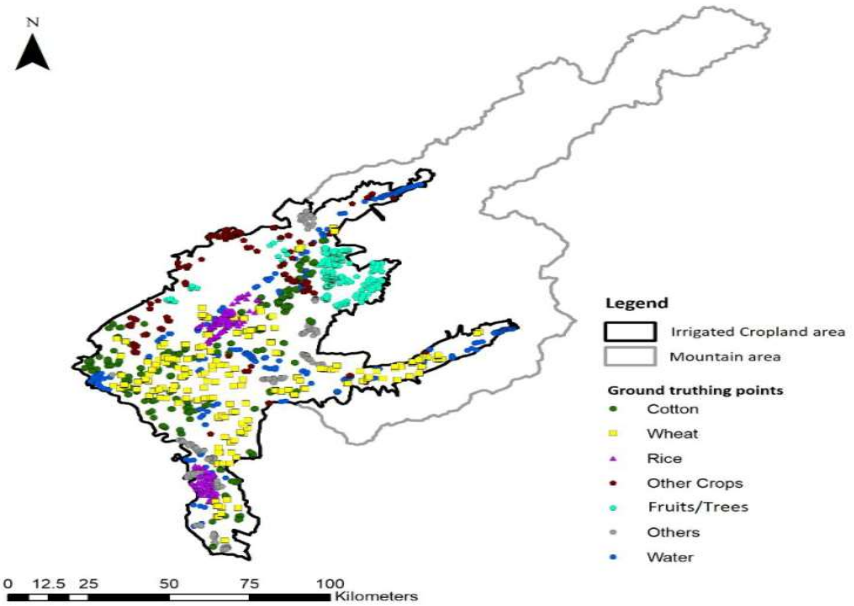


Figure 4.18. The result of the classification of agricultural products for the entire Tashkent region, obtained on the basis of the EVI and NDVI indices

Conclusion to Chapter 4

1. For atmospheric correction, an experimental study of the proposed method based on the architecture of the encoder - decoder neural network was carried out. This new method avoids the use of interactive correction programs. The accuracy of this method was 90.5% compared to the result of the interactive program (Sen2Core), which shows its adequacy. The proposed method makes it possible to automate the process of atmospheric correction of "raw" satellite images and to abandon the use of interactive programs that require user participation. In addition, this method makes it possible to carry out atmospheric correction of images obtained from different satellites in a single way and unify the correction result.
2. Two different methods were used to classify agricultural areas and products. Firstly, the VI indices were used to determine the condition and productivity of agricultural land. Secondly, the data obtained on the basis of the VI indices were used to train a neural network with a modified VGG architecture. As a result, it was possible to identify the types of agricultural products cultivated in the study area. The accuracy of the result was 88%. This accuracy is acceptable for determining the distribution of agricultural product types over relatively large areas.
3. A new method based on neural networks for tracking urban and rural areas, detecting objects and tracking changes in cities has been experimentally investigated. For this purpose, the U-Net and MobileNet encoder-decoder architectures were used. At the first stage, the data was trained using the U-Net architecture. The accuracy of the result obtained from the application of the U-Net architecture was 89%. To increase accuracy, within the framework of the U-Net architecture, its coding part has been replaced by an encoding part based on the MobileNet network architecture. The conducted experimental study showed an improvement in segmentation accuracy by 4.4%.

CONCLUSION

The presented dissertation is a study devoted to the development of methods and tools for processing data obtained from satellites in order to monitor vast territories. The main scientific and applied results of this work can be described as follows:

1. An atmospheric correction method for processing satellite images has been developed and implemented. This method allows to obtain satellite images that are not affected by the properties of the atmosphere, and also makes it possible to unify images obtained from different satellites. At the same time, it is possible, without involving existing interactive programs, to carry out automatic atmospheric correction of images for which it is missing.
2. A method based on modification of the architecture of a deep learning neural network is proposed and implemented, which allows segmentation and identification of objects in territories, including urban and agricultural areas. The method makes it possible to increase the accuracy of the results and significantly reduce the requirements for computing resources needed to solve such problems.
3. Methods for assessing the state of agricultural zones and classifying crops using algorithms for determining vegetation indices and deep learning methods are proposed and implemented. The methods allow us to obtain objective information about the distribution and condition of agricultural land, cultivated crops, as well as about the distribution of urban land.
4. An experimental study of all proposed methods implemented in the form of appropriate software has been conducted. This study showed an increase in the accuracy of satellite image processing results compared to existing methods. This implementation has made it possible to reduce the requirements for computing resources in both memory and hardware support for computing.

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APPLICATION

РОССИЙСКАЯ ФЕДЕРАЦИЯ

СВИДЕТЕЛЬСТВО

о государственной регистрации программы для ЭВМ

№ 2023664858

«Программа для распознавания и сегментации объектов на спутниковых снимках» (SatObj)

Правообладатель: ***федеральное государственное бюджетное образовательное учреждение высшего образования "Санкт-Петербургский государственный университет" (СПбГУ) (RU)***

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Ю.С. Зубов

РОССИЙСКАЯ ФЕДЕРАЦИЯ

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ФЕДЕРАЛЬНАЯ СЛУЖБА
ПО ИНТЕЛЛЕКТУАЛЬНОЙ СОБСТВЕННОСТИ

ГОСУДАРСТВЕННАЯ РЕГИСТРАЦИЯ ПРОГРАММЫ ДЛЯ ЭВМ

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Название программы для ЭВМ:
«Программа для распознавания и сегментации объектов на спутниковых снимках» (SatObj)

Реферат:
Программа «SatObj» является программой обработки изображений Земли, получаемых при спутниковм мониторинге определенных районов земной поверхности. Программа предназначена для автоматической сегментации спутниковых снимков на которых могут присутствовать следующие типы земной поверхности — сельскозозяйственные земли, пастбища, бесплодные земли, здания и сооружения, лесные массивы, водные массивы. Остальные типы, не входящие в этот перечень, отображаются как неизвестный тип. Программа выполняет следующие функции: создает глубокую нейронную сеть, с помощью которой происходит сегментация спутниковых изображений; реализует алгоритм обучения нейронной сети по имеющемуся набору размеченных данных спутниковых изображений; с помощью обученной нейронной сети определяет тип земной поверхности для каждого пикселя предъявляемого изображения и формирует карту распределения типов повехности на спутниковом изображении.

Язык программирования: Python 3.7

Объем программы для ЭВМ: 17 МБ