ГЕОЛОГИЯ, ПОИСКИ И РАЗВЕДКА ТВЕРДЫХ ПОЛЕЗНЫХ ИСКОПАЕМЫХ, МИНЕРАГЕНИЯ

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Scientific original article

MONITORING FOREST FUND LANDS USING REMOTE SENSING COMBINED WITH COLLECTEARTH POINT DATA

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Abstract

Uzbekistan's mountainous forests, particularly within the Gissar Range, provide vital ecosystem services such as soil erosion control and biodiversity conservation. However, these semi-arid ecosystems are increasingly pressured by anthropogenic activities, necessitating efficient monitoring tools. This study develops a robust methodology for forest area evaluation in the Dekhkanabad forestry organization using a multi-source remote sensing approach. The methodology integrates Sentinel-2 multispectral imagery with high-resolution Kompsat-3 data and topographic variables derived from an ALOS PALSAR Digital Elevation Model (DEM). To address the spectral heterogeneity of the mountainous terrain, an Object-Based Image Analysis (OBIA) framework was employed. Ground truth data were established using the FAO's Collect Earth tool, through which 1,980 plots were classified according to IPCC and FAO Forest Resources Assessment guidelines. A supervised classification model was implemented using a 70/30 training-to-validation split. The results yielded an overall accuracy of 76 % and a Kappa coefficient of 0.66. While Pasture and Cropland classes showed high reliability, the Forest class (0.198 error) experienced spectral confusion with pastures due to the "open-canopy" nature of local juniper forests, where the understory influences the spectral signature. Settlements presented the highest classification challenge (0.731 error) due to spectral mixing with rural vegetation. Despite these challenges, the OBIA approach significantly reduced "salt-and-pepper" noise and improved boundary definition compared to pixel-based methods. This study provides a cost-effective, statistically reliable baseline for the Dekhkanabad State Forest Fund, offering a scalable workflow for sustainable forest management and conservation planning in Central Asia's semi-arid regions.

Keywords: Remote sensing, object-based image analysis (OBIA), land cover mapping, forest types, forest fund lands, Uzbekistan, Dekhkanabad, Sentinel-2, Kompsat 3, CollectEarth

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Научная оригинальная статья

МОНИТОРИНГ ЗЕМЕЛЬ ЛЕСНОГО ФОНДА С ПОМОЩЬЮ ДИСТАНЦИОННОГО ЗОНДИРОВАНИЯ В СОЧЕТАНИИ С ТОЧЕЧНЫМИ ДАННЫМИ COLLECTEARTH

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Аннотация

Горные леса Узбекистана, особенно в пределах Гиссарского хребта, играют ключевую роль в предоставлении жизненно важных экосистемных услуг, таких как предотвращение эрозии почвы и сохранение биоразнообразия. Однако эти полуаридные экосистемы подвергаются растущему антропогенному воздействию, что обуславливает необходимость внедрения эффективных инструментов мониторинга. В данном исследовании разработана надежная методология оценки лесных площадей Дехканабадского государственного лесного хозяйства с использованием многосенсорного подхода дистанционного зондирования. Методология интегрирует мультиспектральные снимки Sentinel-2 с данными высокого разрешения Kompsat-3 и топографическими переменными, полученными на основе цифровой модели рельефа (ЦМР) ALOS PALSAR. Для учета спектральной неоднородности горной местности был применен объектно-ориентированный анализ изображений (OBIA). Опорные данные были собраны с помощью инструмента Collect Earth (ФАО), в рамках которого 1980 участков были классифицированы в соответствии с руководящими принципами МГЭИК и Глобальной оценки лесных ресурсов (FRA) ФАО. Модель контролируемой классификации была реализована с разделением данных на обучающую и валидационную выборки в соотношении 70/30. Результаты показали общую точность классификации 76 % при коэффициенте Каппа 0,66. В то время как классы «Пастбища» и «Пахотные земли» продемонстрировали высокую надежность, класс «Лес» (ошибка 0,198) подвергался спектральному смешению с пастбищами. Это объясняется редколесной структурой местных арчовых лесов, где травянистый покров под пологом деревьев влияет на спектральную сигнатуру. Наибольшие трудности вызвал класс «Населенные пункты» (ошибка 0,731) из-за смешения спектральных характеристик строений и сельской растительности. Несмотря на это, подход OBIA значительно снизил уровень цифрового шума и улучшил определение границ объектов по сравнению с попиксельными методами. Данное исследование формирует экономически эффективную и статистически надежную базу для мониторинга Дехканабадского лесного фонда.

Ключевые слова: Дистанционное зондирование, объектно-ориентированный анализ изображений (OBIA), картирование растительного покрова, типы лесов, земли лесного фонда, Узбекистан, Дехканабад, Sentinel-2, Kompsat 3, CollectEarth

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1. Introduction

A landlocked country in Central Asia, Uzbekistan possesses diverse landscapes, including arid plains, mountainous regions, and riverine ecosystems. While traditionally known for its vast deserts, Uzbekistan also harbors significant forest resources, particularly in its mountainous areas (e.g., Western Tien Shan, Gissar-Alai ranges) and along river floodplains (e.g., Amu Darya and Syr Darya river basins) [3]. Though often fragmented and under pressure from anthropogenic activities such as agriculture, urbanization, and fuelwood collection, these forests provide critical ecological services, including biodiversity conservation, soil erosion control, water regulation, and carbon sequestration.

Accurate and regular assessment of forest cover is a prerequisite for effective forest management and conservation. Traditional ground-based surveys are labor-intensive, time-consuming, and often logistically challenging, especially in remote or inaccessible areas. Remote sensing technologies, particularly satellite imagery, offer a cost-effective and efficient alternative for large-scale and repetitive forest monitoring [1,3]. The advent of free and openly accessible satellite data, such as that provided by the European Space Agency's (ESA) Sentinel-2 mission, has revolutionized land cover mapping and environmental monitoring [2].

Sentinel-2, with its multispectral instrument (MSI) capturing data across 13 spectral bands with spatial resolutions ranging from 10 to 60 meters, provides a rich source of information for vegetation analysis. Its frequent revisit time (5 days at the equator with two satellites) ensures the availability of cloud-free imagery, crucial for monitoring dynamic forest environments. This study aims to leverage Sentinel-2 data and various index-based methods to develop a robust methodology for forest area evaluation and mapping in Uzbekistan. The objective is to provide a comprehensive and accurate assessment of forest distribution, aiding in the sustainable management and conservation of these vital ecosystems.

2. Materials

2.1. Study Area

This study evaluates forestry areas within the Dekhkanabad forestry organization in Uzbekistan's Kashkadarya region. Located in the southeast of the region, within the Dekhkanabad district, the forestry spans the slopes of the Gissar Range. The territory is mountainous with diverse altitudes and natural conditions, featuring three relief types: low-mountain (dissected ridges and adyrs up to 1,500 meters, of denudation-tectonic origin), mid-mountain (slopes of denudation-tectonic origin), and high-mountain (alpine areas above 3,000 meters, occupying relatively small areas).

The total land area of the Dehkanabad State Forest Fund is 109,392 hectares, of which 55,689 hectares are forested, 28,068.9 hectares are pastures, and 33,467.7 hectares are other non-agricultural lands. Forests account for 73.6 % of the total forest area, or 55,689 hectares. 36.3 % of the area is non-forested, or 20,229.5 hectares. Cultivated forests account for 1.2 % of the forest area, or 671.7 hectares.

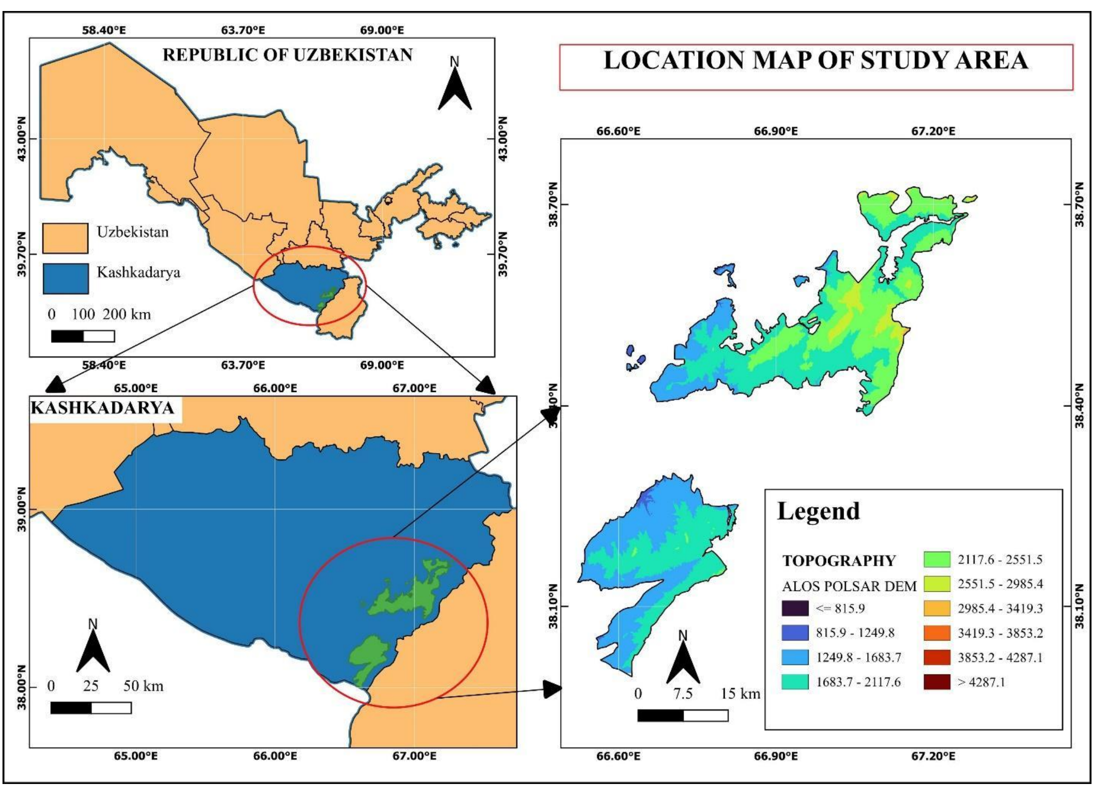

Fig. 1. Study area location

Рис. 1. Местоположение области исследования

The forest plantation region of the forestry enterprise is favorable for the successful growth of tree species such as juniper, walnut, hawthorn, and fruit trees, allowing for the creation of highly productive plantations of these species on the territory of the forestry enterprise.

2.2. Satellite Data Acquisition

Effective use of remote sensing data from multiple sources relies on rigorous pre-processing methodologies to ensure data quality, geometric accuracy, and spectral consistency, thereby optimizing their usefulness for subsequent analysis. In this study, Sentinel-2 and Kompsat-3 imagery, augmented with an ALOS PALSAR-derived digital elevation model (DTM) and auxiliary GIS data, underwent a series of specialized pre-processing steps. Sentinel-2 Level-2A data, already atmospherically corrected, were initially subjected to an atmospheric correction check through visual inspection and comparison with ground truth data; where inconsistencies were detected, the FLAASH module in ENVI was used for re-calibration. Subsequent refinement of the geometric correction involved the use of ground control points (GCPs) derived from high-resolution orthorectified imagery and GIS layers, achieving a root mean square error (RMSE) below 0.5 pixels to ensure accurate spatial alignment. The corresponding spectral bands were then stacked to create a multispectral image, after which all bands were resampled to a uniform 10-meter spatial resolution using the nearest neighbor method to preserve the original spectral values.

Complementing Sentinel-2, Kompsat-3 images, offering improved spatial resolution, were processed using rigorous geometric correction, again aiming for an RMSE below 0.5 pixels, after

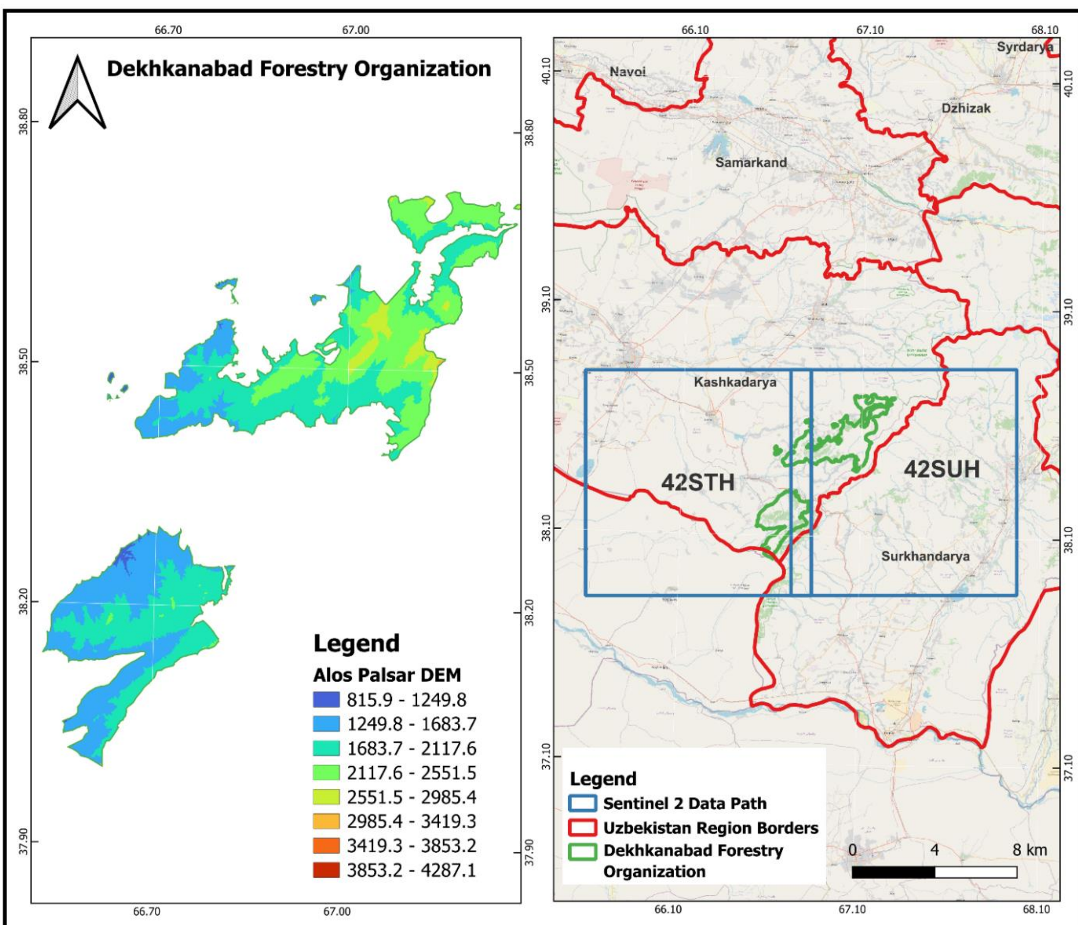

Fig. 2. Location of the area of interest and Sentinel 2 data path

Рис. 2. Расположение исследуемой территории и путь доступа к данным Sentinel-2 which atmospheric correction was performed using the FLAASH module to obtain surface reflectivity values. In addition, the Gram-Schmidt pan-sharpening technique was applied to merge the multispectral and panchromatic bands, resulting in a high-resolution multispectral image.

The ALOS PALSAR L1.1 data, critical for obtaining topographic information, are radiometrically calibrated and geometrically corrected using Range-Doppler terrain correction, followed by interferometric processing to create an interferogram and a wrapped phase image. The phase unwrapping resolves phase ambiguities, and the wrapped phase image is geocoded to create a georeferenced DEM. This original DEM is then filtered to reduce noise, smoothed to minimize artifacts, and void filled using interpolation techniques to ensure a complete and accurate representation of the terrain. The culmination of these pre-processing steps is a carefully prepared dataset ready for subsequent feature extraction, image classification, and spatial analysis.

2.3. Pre-processing

Sentinel-2 Level-2A data are already atmospherically corrected [2,6,7,9]. Resampling bands with different spatial resolutions to a common resolution (10m) for consistent analysis was done [5].

2.4. Training data

This study leverages Collect Earth, an open-source tool developed by the Food and Agriculture Organization (FAO) and Google, for collecting ground truth data within the Dekhkanabad forestry area. Collect Earth allows for efficient and systematic visual interpretation of high-resolution satellite imagery, facilitating the creation of a spatially explicit database of land cover types. A total of 1,980 Collect Earth plots were interpreted and classified according to a predefined classification scheme, aligning with both Intergovernmental Panel on Climate Change (IPCC) and FAO Forest Resources Assessment (FRA) guidelines (Fig 3). This robust dataset provides the necessary ground truth for training and validating the supervised object-based classification model. The classification stage used 70 % of the training data, with the remaining 30 % reserved for validation.

The classification scheme used in Collect Earth incorporated the following land cover categories:

1. Forest: Land covered with forest, characterized by a dominance of tree vegetation.

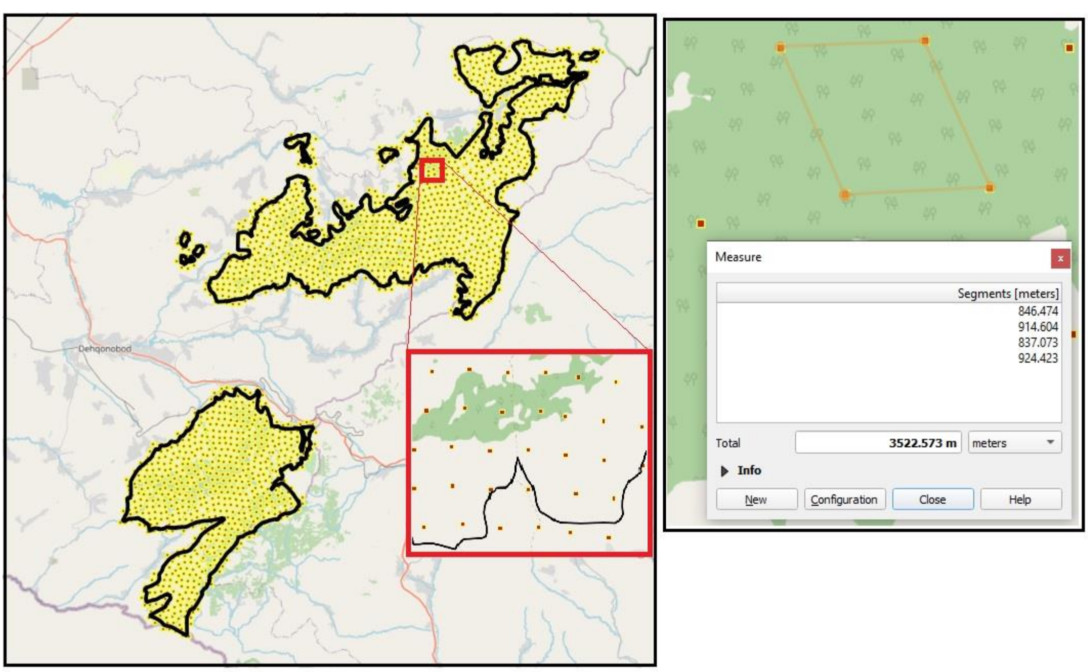

Fig. 3. Generated 0.8 by 0.8 km grid points CollectEarth

Рис. 3. Сгенерированые CollectEarth точки сетки размером 0,8 на 0,8 км

2. Cropland: Land that is regularly cultivated for the purpose of growing crops. This includes both annual and perennial crops.

3. Pasture: Areas of land covered with perennial grasses or forbs. Pastures and permanent pastures include both manicured and unmanicured areas used for grazing livestock.

4. Wetlands: Land covered or saturated with water in whole or in part throughout the year. This category encompasses marshes, swamps, bogs, and similar ecosystems.

5. Settlement: Land that is part of an urban or rural residential setting. This includes buildings, roads, and associated infrastructure within residential areas.

6. Other Land: Land not included in other categories. This residual category encompasses a diverse range of land cover types such as barren land, rock outcrops, and sparsely vegetated areas (Fig 3).

The use of Collect Earth enabled a systematic and consistent approach to ground truth data collection. The tool's ability to overlay high-resolution imagery (e.g., from Google Earth) with plot boundaries and pre-defined classification schemes ensured that the interpreter could accurately and efficiently assign land cover classes to each plot. Furthermore, the integration with Open Foris facilitates data management and analysis, streamlining the process of utilizing ground truth data for land cover mapping and monitoring. The reliance on the IPCC and FAO FRA classification types ensures the comparability of the results with international standards and reporting frameworks.

3. Methodology

3.1. Justification of Spectral Indices and Topographic Data Selection

The landscape of Uzbekistan presents a complex challenge for Land Use and Land Cover (LULC) classification due to its semi-arid environment, where spectral confusion frequently occurs between sparse natural forests, shrublands, and irrigated agriculture. To address the spectral heterogeneity of these classes, this study moves beyond standard spectral bands by integrating a specific suite of vegetation indices [10] and topographic data derived from ALOS PALSAR.

For many years, remote sensing imagery has played an essential role in forest inventory and mapping practices, especially in numerous developed nations. The information gleaned from these images has become indispensable for understanding and managing forest resources. The application of automated processing techniques to these images offers the potential for considerable cost reductions, particularly within the increasingly digital data interpretation environment that is becoming standard practice. As data analysis shifts toward digital platforms, the efficiency and economy provided by automation become increasingly significant. Reference [9] highlights the importance of these cost savings and their connection to the growing digitalization of data interpretation workflows.

However, automated procedures that rely solely on analyzing individual pixels often fall short of achieving the desired level of accuracy. This limitation stems from their failure to account for the spatial arrangement and textural characteristics of the landscape. While spectral information is important, the context provided by spatial relationships and textural patterns is equally crucial for accurate classification. To achieve effective automated classification of landscape structures, it is necessary to identify and incorporate the spectral, textural, and geometric features that characterize different land cover classes. The unique combination of these features allows for better differentiation between various land cover types.

One of the challenges in this process is the potential for overlapping spectral curves between different land cover classes. This spectral similarity can make it difficult to distinguish accurately between these classes based solely on their spectral signatures. Differentiating between species or forest types based on spectral signature can be particularly challenging. Nevertheless, with a well-defined, confident methodology, coupled with the appropriate level of experience and expertise, this problem can be effectively addressed and overcome. Careful analysis and nuanced approaches are required to leverage spectral information effectively in the face of these challenges.

The creation of meaningful objects within the image analysis process fundamentally involves identifying and analyzing changes in the heterogeneity or homogeneity of the image features.

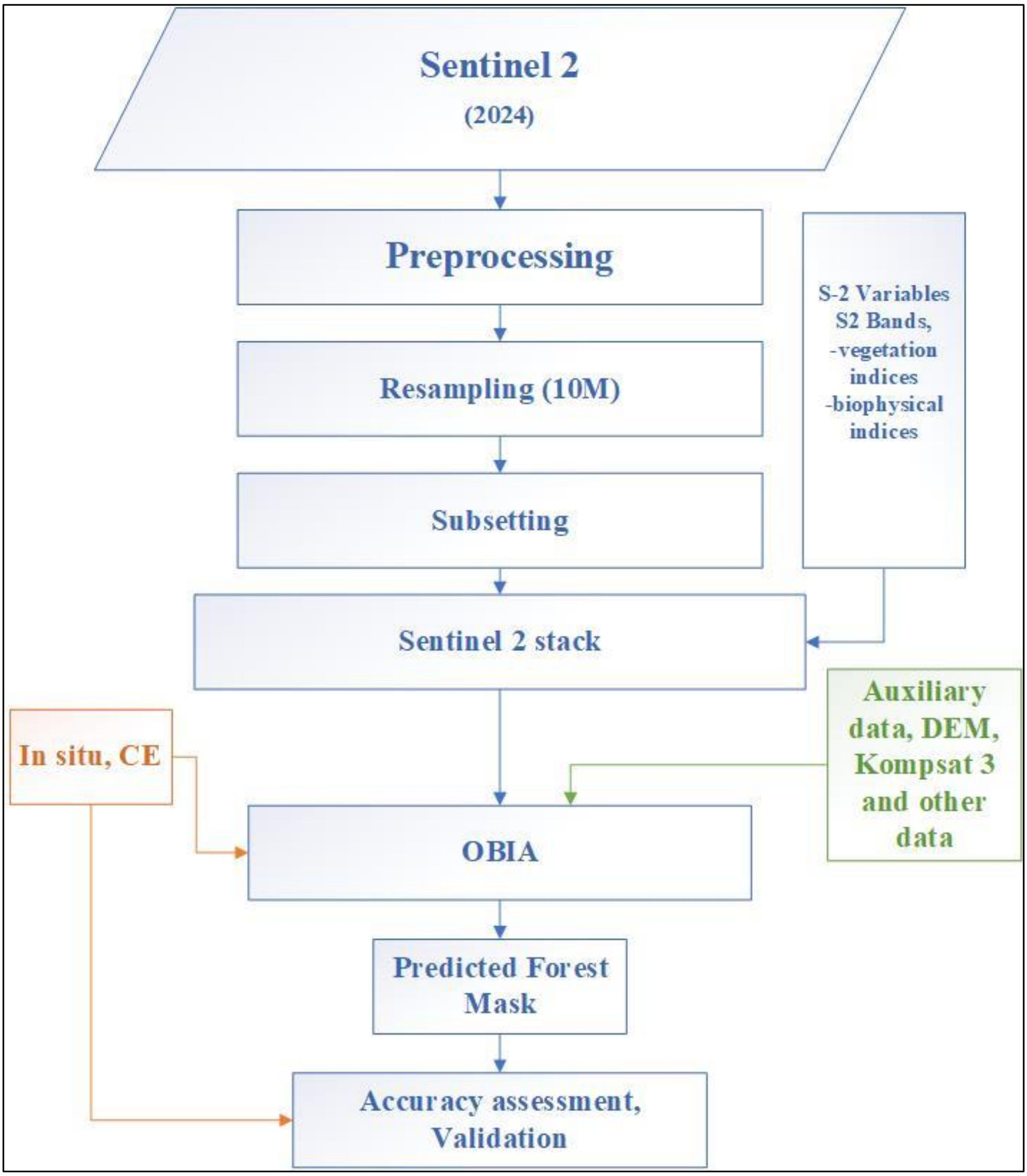

Fig. 4. Overall flowchart of the study

Рис.4. Общая блоксхема исследования

By detecting shifts in these characteristics, it becomes possible to delineate distinct objects and extract valuable information. Over time, several sophisticated segmentation methods have been developed to facilitate this process [11, 12]. Common approaches within these segmentation methods typically involve techniques such as thresholding, which separates pixels based on intensity values, or area enhancement algorithms, which highlight regions of similar characteristics. Different types of texture segmentation algorithms are also frequently employed, leveraging the patterns and variations in image texture to delineate objects.

Beyond these automated techniques, knowledge-based approaches also play a vital role in operational applications. These approaches incorporate expert knowledge and contextual information to guide the segmentation and classification processes. Baatz and Schepe [11] introduced a multi-resolution segmentation algorithm, a key innovation in the field. This algorithm was first implemented in the commercial object-oriented image analysis software known as eCognition [12, 13], showcasing its practical application and impact. The object classification procedure implemented in this software considers not only the spectral and texture properties of image objects, but also their size and behavior across different scale levels. This multi-scale analysis allows for a more comprehensive and robust classification process.

The core principle of the algorithm is to build image objects in a stepwise manner, systematically minimizing their weighted heterogeneity. This ensures that the resulting objects are as internally consistent as possible. Current object-based approaches are typically based on the creation of initial object primitives. These primitives are then subjected to a step-by-step reconstruction process, utilizing region-specific supervised methods at multiple levels. This iterative refinement process allows for the creation of highly accurate and meaningful image objects.

The supervised object-based classification approach leverages several key data sources. These include spectral information derived from Sentinel-2 and Kompsat 3 imagery, elevation data obtained from a digital terrain model (DTM) generated from ALOS PalSAR data, and auxiliary GIS data, which provides additional contextual information. Combining these diverse data sources enables a more comprehensive and accurate classification process [14,15,16,17,18,19].

High spatial resolution satellite imagery, particularly that with four bands in the near-infrared electromagnetic region and two additional bands in the shortwave infrared region, can serve as a sufficient data source for automated forest boundary delineation [20,21]. The level of detail captured by these images allows for precise identification of forest boundaries. To demonstrate this capability, several Sentinel-2 scenes from the summers of 2024, encompassing the territory of Dehkanabad forestry, were processed and analyzed. These images provided valuable data for mapping and monitoring forest resources in the region.

3.3. Accuracy Assessment

The accuracy of the resulting forest maps was assessed using validation points, representing 30 % of the total number of points used in training, compared with the classification results. Validation yielded an overall accuracy of 76 %, indicating a high match between the predicted forest types and actual site conditions. Further analysis revealed that user accuracy for individual forest classes ranged from 83 % to 92 %, with the lowest accuracy observed for deciduous forests, likely due to their spectral similarity to other land-use types. The kappa coefficient, a measure of agreement accounting for chance, was calculated as 0.66, indicating a significant level of agreement between the classification results and the validation data. These accuracy metrics demonstrate the reliability and usefulness of the resulting forest maps for a variety of applications, including forest management, conservation planning, and environmental research.

Table 1

Confusion Matrix for Land Cover Classification and CollectEarth Points

Таблица 1

Матрица ошибок для классификации типов землепользования и точек CollectEarth

Land Cover Class	*Cropland*	*Forest*	*Pasture*	*Settlement*	*Other land*	*Wetland*	*Classification Class Error*
Cropland	448	0	50	3	2	1	0.111
Forest	2	514	120	5	0	0	0.198
Pasture	33	74	1372	31	1	0	0.091
Settlement	21	27	313	133	1	0	0.731
Otherland	28	1	26	2	64	0	0.471
Wetland	4	1	7	2	1	0	1.000

3.3.1. High-Performing Classes (Pasture and Cropland)

The model demonstrated its highest reliability in identifying Pasture (0.091 error) and Cropland (0.111 error).

Pasture had the highest number of correctly classified points (1,372), indicating that its spectral signature is well-defined in the study area.

Cropland also showed strong stability, with only minor confusion with Pasture, likely due to the similar greenness of irrigated crops and mountain grasses.

3.3.2. The Forest-Pasture Overlap

The Forest class achieved a respectable error rate of 0.198, but the matrix reveals a specific challenge: 120 forest points were misclassified as Pasture.

This confusion is likely due to the "open-canopy" nature of the Dekhkanabad juniper forests. In these areas, the satellite captures a "mixed pixel" containing both tree cover and the grass/pasture growing underneath, leading the classifier to misidentify sparse woodlands as open grassland.

3.3.3. Challenges with Settlements and Other Land

The Settlement class faced significant difficulty with a high error rate of 0.731.

The matrix shows that 313 settlement points were misclassified as Pasture. In rural Uzbekistan, settlements often consist of houses interspersed with large gardens and grazing patches. This "spectral mixing" makes it difficult for a 10-meter resolution sensor (Sentinel-2) to distinguish a sparse village from a grassy field.

Other Land (barren/rocky) also showed high error (0.471), frequently being confused with Cropland and Pasture, likely due to sparse vegetation growing on rocky soils.

3.3.4. Statistical Limitations (Wetland)

The Wetland class had a 100 % error rate. This is primarily a result of a very low sample size (only 15 total points across all categories). In a semi-arid mountainous region like Dekhkanabad, wetlands are rare and small; the model likely lacked enough training data to create a distinct spectral profile for this class.

4. Results and Discussion

4.1. Land Cover Classification Performance

The implemented workflow (Figure 3) integrates Sentinel-2 multispectral data (2024), preprocessing (atmospheric verification, geometric correction), 10 m resampling, subsetting, and band stacking, followed by feature integration (vegetation indices, biophysical variables), auxiliary DEM and Kompsat-3 data, and supervised OBIA classification using Collect Earth reference samples.

The object-based framework successfully delineated spatially coherent land cover patches across heterogeneous mountainous terrain. Compared to pixel-based classification approaches, OBIA reduced salt-and-pepper noise and improved boundary definition, particularly along forest–pasture transition zones.

The resulting **forest mask** spatially corresponds to juniper-dominated mountainous slopes and valley forest fragments, consistent with known ecological distribution patterns of the Gissar Range.

4.2. Synthesis of Classification Failures

The analysis of the classification accuracy reveals that the Settlement and Wetland classes experienced the highest error rates, with values of 0.731 and 1.000, respectively. These results highlight fundamental methodological and data-related limitations when using 10-meter resolution multispectral satellite imagery, such as data from the Sentinel-2, in heterogeneous and semi-arid landscapes.

Settlement Class: Spectral Fragmentation and Mixed Pixels

The high error rate observed in the Settlement class is primarily attributed to the phenomenon known as spectral fragmentation. In semi-arid environments, rural settlements typically consist of small, dispersed buildings surrounded by vegetation patches, bare soil, and agricultural land. At a spatial resolution of 10 meters, a single pixel often contains a mixture of several land-cover components, resulting in mixed spectral signatures.

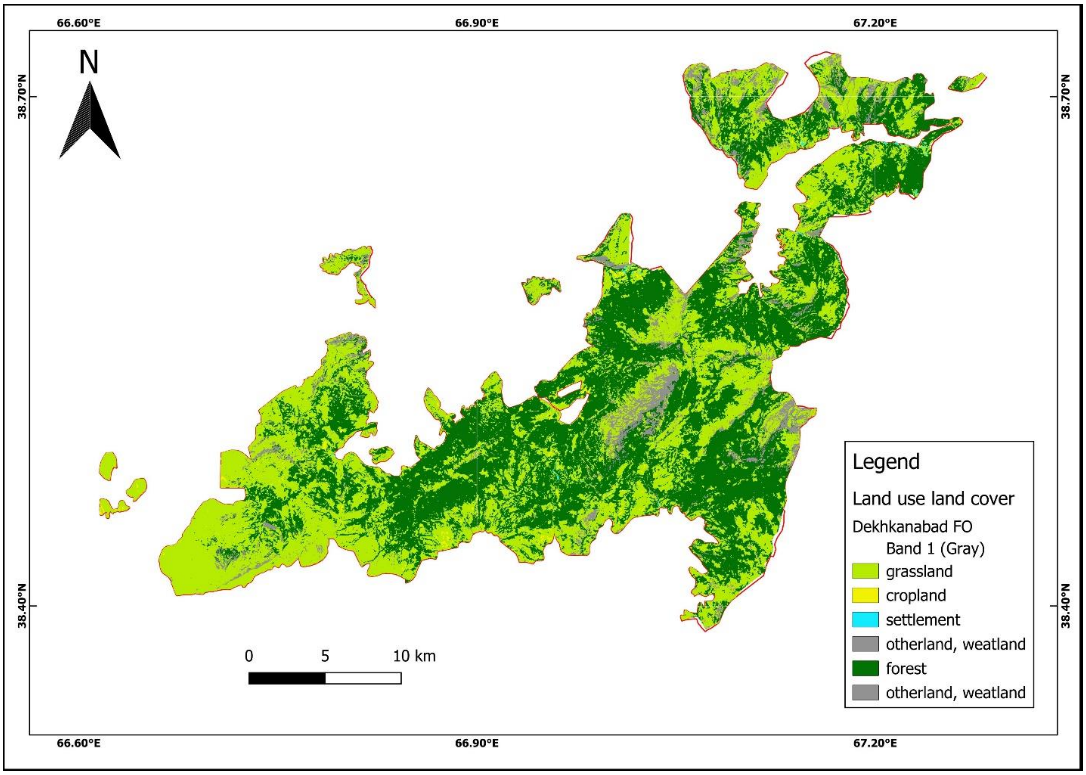

Fig. 5. Classification results (north part of the forestry organization)

Рис. 5. Результаты классификации (северная часть лесохозяйственной организации)

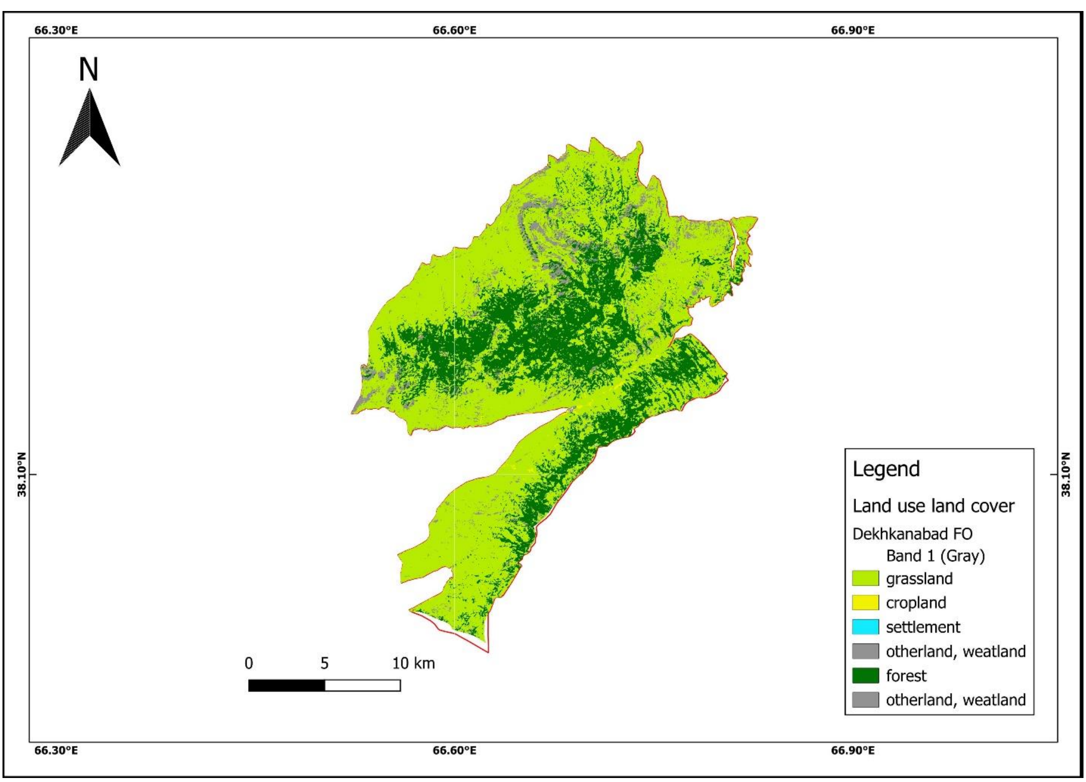

Fig. 6. Classification results (south part of the forestry organization)

Рис. 6. Результаты классификации (южная часть лесохозяйственной организации)

In the study area, building materials such as clay, brick, or concrete exhibit spectral characteristics that are frequently similar to surrounding bare soil or dry vegetation. Consequently, the classifier struggles to distinguish settlement pixels from adjacent land-cover classes. This issue becomes more pronounced in rural mountainous landscapes where settlements are small and spatially fragmented. The classification algorithm therefore tends to misclassify settlement areas as bare land, cropland, or sparse vegetation, leading to significant omission and commission errors.

Another contributing factor is the limited representation of settlement features in the training dataset. When training samples do not adequately capture the variability of settlement surfaces (e.g., roofs, roads, courtyards), the classifier cannot construct a stable statistical model for this class.

Wetland Class: Statistical Insufficiency and Sample Scarcity

The Wetland class exhibited the highest error rate, reaching 1.000, indicating that the classifier failed to correctly identify wetland pixels. This failure is primarily due to insufficient training data. With only 15 training points, the model lacked enough examples to establish a reliable statistical representation of wetland spectral characteristics.

Wetlands in semi-arid regions are typically spatially limited and highly dynamic, often appearing as small riparian zones along rivers, seasonal marshes, or temporary water-logged areas. Such environments are difficult to capture using sparse ground reference points. In addition, the spectral signature of wetlands may overlap with other classes such as dense vegetation or irrigated agricultural fields, further complicating classification.

4.3. Potential Improvements for Future Classification

Integration of Ancillary Vector Data

One effective strategy for improving settlement detection is the incorporation of ancillary vector datasets. External spatial datasets can provide explicit structural information that is not detectable through spectral reflectance alone. For instance, settlement areas can be enhanced by integrating building footprints or road networks derived from the collaborative mapping platform OpenStreetMap.

2. Hydrological Indicators for Wetland Detection

For improving wetland classification, it is essential to integrate hydrologically sensitive indices derived from multispectral imagery. One widely used index is the Normalized Difference Water Index, which enhances the spectral contrast between water bodies and surrounding land surfaces.

The NDWI exploits differences in reflectance between the green and near-infrared bands, allowing the detection of water-rich surfaces even when they occupy a small proportion of the pixel. Incorporating NDWI as an additional input band in the classification process can significantly improve the identification of wetlands and other water-related features.

Additionally, existing hydrographic vector datasets–including river networks and permanent water bodies–can be integrated into the classification framework. These datasets provide spatial constraints that help guide the model toward areas where wetlands are more likely to occur.

3. Increasing Training Sample Density

Another critical improvement involves expanding the training dataset, particularly for underrepresented classes such as wetlands and settlements. Increasing the number of training points allows the classifier to better capture intra-class variability and improve statistical robustness.

4. Incorporating Multi-Temporal and Multi-Source Data

Future studies may also benefit from integrating multi-temporal satellite observations, which capture seasonal variations in vegetation and moisture conditions. This approach can improve the discrimination of wetlands that appear only during certain periods of the year.

Furthermore, combining optical data with radar observations from missions such as Sentinel-1 can enhance classification performance. Radar imagery is particularly useful for detecting surface moisture and water bodies, even under vegetation cover or cloud conditions.

The generated map and statistics provide a vital baseline for the Dekhkanabad State Forest Fund. With forests officially accounting for 73.6 % of the forest fund area (as noted in Section 2.1), the ability to monitor these resources remotely is crucial. The current methodology offers a cost-effective alternative to labor-intensive ground surveys.

5. Conclusion

The proposed workflow demonstrates that combining Sentinel-2 multispectral imagery, DEM-derived terrain variables, and Collect Earth validation within an OBIA framework provides a statistically reliable and ecologically interpretable approach for forest land monitoring in semi-arid mountainous regions.

The achieved overall accuracy (76.6 %) and substantial Kappa agreement (0.66) confirm the operational suitability of the method, while the identified error patterns provide a clear roadmap for methodological refinement in future studies.

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