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USING GOOGLE EARTH ENGINE AND RANDOM FOREST FOR CADASTRAL MONITORING OF AGRICULTURAL LANDS IN ALMATY REGION

АЛМАТЫ ОБЛЫСЫНЫҢ АУЫЛ ШАРУАШЫЛЫҒЫ ЖЕРЛЕРІН КАДАСТРЛЫҚ МОНИТОРИНГТЕУДЕ GOOGLE EARTH ENGINE ЖӘНЕ RANDOM FOREST ӘДІСІН ҚОЛДАНУ

ИСПОЛЬЗОВАНИЕ GOOGLE EARTH ENGINE И RANDOM FOREST ДЛЯ КАДАСТРОВОГО МОНИТОРИНГА СЕЛЬСКОХОЗЯЙСТВЕННЫХ ЗЕМЕЛЬ АЛМАТИНСКОЙ ОБЛАСТИ

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Region, remote sensing.

ABSTRACT

The article develops a cloud-based workflow for preliminary cadastral monitoring of agricultural lands in Almaty Region using Google Earth Engine and the Random Forest algorithm. The study focuses on the remote-sensing diagnosis of actual land-surface conditions rather than on potential land suitability assessment. Landsat 8/9 Surface Reflectance images were processed for 2015, 2020 and 2025, and Sentinel-2 imagery was used as an auxiliary visual reference for sample interpretation. Seasonal composites were generated, cloud-contaminated pixels were masked, and NDMI and BSI indicators were calculated to describe moisture-related conditions and exposed or sparsely covered surfaces. The spectral bands and derived indicators were then combined in a Random Forest classifier to distinguish four monitoring classes: stable vegetation cover, open or sparsely covered soil, water bodies, and built-up or non-agricultural areas. Validation was performed using an independent sample, and class areas were calculated from the classified raster. The resulting map is proposed as a diagnostic layer for identifying territories that may require additional cadastral or field verification. The approach does not replace official cadastral records, but it supports land-use control through reproducible satellite-based evidence.

Түйінді сөздер:

Google Earth Engine,
кадастрлық мониторинг,
ауыл шаруашылығы
жерлері, Random Forest,

ТҮЙІНДЕМЕ

Мақалада Алматы облысының ауыл шаруашылығы жерлерін алдын ала кадастрлық мониторингтеу үшін Google Earth Engine платформасы мен Random Forest алгоритміне негізделген бұлттық жұмыс барысы ұсынылады. Зерттеу жердің әлеуетті жарамдылығын



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NDMI, BSI, Алматы
облысы, қашықтан
зондтау.

ғын бағалауға емес, ауыл шаруашылығы аумақтарындағы жер бетінің нақты жағдайын қашықтан зондтау деректері арқылы диагностикалауға бағытталған. 2015, 2020 және 2025 жылдарға арналған Landsat 8/9 Surface Reflectance деректері өңделіп, Sentinel-2 суреттері оқыту үлгілерін визуалды нақтылау үшін қосымша дереккөз ретінде пайдаланылды. Әр жыл бойынша маусымдық композиттер қалыптастырылып, бұлтпен жабылған пиксельдер маскаланған, сондай-ақ ылғалдылық жағдайын сипаттайтын NDMI және ашық немесе сирек өсімдік жамылғысымен жабылған беттерді анықтайтын BSI индекстері есептелді. Спектрлік арналар мен есептелген индекстер Random Forest классификаторында біріктіріліп, төрт мониторингтік класс ажыратылды: тұрақты өсімдік жамылғысы, ашық немесе сирек жабылған топырақ, су объектілері және салынған немесе ауыл шаруашылығына жатпайтын аумақтар. Жіктеу нәтижелері тәуелсіз тексеру үлгісі арқылы бағаланып, әр класс бойынша аудан есептелді. Алынған карта ресми кадастрлық құжатты алмастырмайды, бірақ қосымша кадастрлық немесе далалық тексеруді қажет ететін аумақтарды анықтауға арналған диагностикалық қабат ретінде пайдаланылуы мүмкін.

Ключевые слова:

Google Earth Engine,
кадастровый
мониторинг,
сельскохозяйственные
земли, Random Forest,
NDMI, BSI,
Алматинская область,
дистанционное
зондирование.

АННОТАЦИЯ

В статье разработан облачный рабочий процесс предварительного кадастрового мониторинга сельскохозяйственных земель Алматинской области с использованием Google Earth Engine и алгоритма Random Forest. Исследование направлено не на оценку потенциальной пригодности земель, а на дистанционную диагностику фактического состояния земной поверхности в пределах сельскохозяйственных территорий. Для анализа были обработаны данные Landsat 8/9 Surface Reflectance за 2015, 2020 и 2025 годы, а снимки Sentinel-2 использовались как дополнительный визуальный источник при интерпретации обучающих участков. Для каждого временного среза сформированы сезонные композиты, выполнено маскирование облачных пикселей, а также рассчитаны индексы NDMI и BSI, характеризующие влажностные условия и распространение открытых либо слабо покрытых растительностью поверхностей. Спектральные каналы и расчетные индексы были объединены в классификаторе Random Forest для выделения четырех мониторинговых классов: устойчивый растительный покров, открытая или слабо покрытая почва, водные объекты, а также застроенные и несельскохозяйственные территории. Достоверность классификации оценивалась с использованием независимой проверочной выборки, а площади классов были рассчитаны по итоговому классифицированному растру. Полученная карта не заменяет официальные кадастровые сведения, но может использоваться как диагностический слой для выявления территорий, требующих дополнительной кадастровой или полевой проверки.

INTRODUCTION

Operational cadastral monitoring of agricultural land requires repeated observation of the actual condition of land surfaces, not only the registration of legal boundaries or land-use categories. For Almaty Region, this task is important because irrigated fields, pasture areas, foothill agricultural zones, water bodies and expanding built-up territories occur within the same administrative space. Satellite observations make it possible to detect spatial signals of moisture deficit, exposed soil and non-agricultural transformation, thereby providing an additional diagnostic layer for cadastral verification (Phiri et al., 2020; Segarra et al., 2020).

Conventional cadastral control is often based on periodic inspections, reports and separate cartographic materials. Such sources are valuable, but they may not provide sufficient temporal consistency for identifying recent changes in agricultural land condition. A reproducible remote-sensing workflow can support this process by producing comparable indicators for different years and by linking the resulting maps with independent validation procedures. For this reason, the present study combines satellite-derived indices, supervised classification and accuracy assessment as complementary components of cadastral monitoring (Congalton, 1991; Foody, 2002; Olofsson et al., 2014).

LITERATURE REVIEW

Google Earth Engine provides a suitable environment for this type of diagnostic analysis because it combines satellite archives, cloud computation and scripted reproducibility. In the present research, the platform is used not as a general GIS modelling tool, but as an operational environment for processing Landsat and Sentinel data, producing seasonal composites, calculating spectral indicators and generating monitoring outputs that can be repeated for subsequent observation periods (Gorelick et al., 2017; Google Developers, 2024).

Machine-learning classification is used here to convert a set of spectral measurements into generalized monitoring classes of land condition. Random Forest was selected because it can handle several predictor bands, reduce sensitivity to noise and operate effectively with reference samples prepared from satellite interpretation (Breiman, 2001; Pal, 2005; Gislason et al., 2006; Belgiu & Dragut, 2016; Maxwell et al., 2018). The aim of the study is to develop a cloud-based cadastral monitoring workflow for agricultural lands in Almaty Region using Google Earth Engine and Random Forest. The research tasks are to create comparable satellite composites for 2015, 2020 and 2025; calculate NDMI and BSI; prepare training and validation samples; classify monitoring classes; assess classification accuracy; and quantify the spatial distribution of the resulting classes. In this workflow, the temporal comparison covers 2015, 2020 and 2025 for NDMI and BSI, whereas the final Random Forest classification, its validation and class-area statistics refer to the 2025 monitoring slice.

MATERIALS AND METHODS

The study was carried out within the administrative boundary of Almaty Region. In this article, the region is considered as a monitoring territory in which spectral conditions of the surface are evaluated through time. The analysis does not aim to determine the legal status or suitability of every land parcel. Instead, it identifies spatial patterns that may indicate stable vegetation cover, exposed soil, water surfaces or built-up and non-agricultural areas requiring further cadastral interpretation.

The methodological sequence included five main operations. First, the study boundary was uploaded to Google Earth Engine and used as a mask for image processing. Second, Landsat images were filtered, cloud-masked and converted into seasonal composites for the selected years. Third, NDMI and BSI were calculated to describe moisture-related conditions and the degree of surface exposure. Fourth, reference samples were used to train and validate the Random Forest classifier. Fifth, the classified map and class-area statistics were prepared for interpretation in the context of cadastral monitoring. The workflow is summarized in Figure 1. For temporal analysis, NDMI and BSI were compared for 2015, 2020 and 2025; the final Random Forest classification and class-area calculation were performed for 2025, the most recent observation year.

Figure 1 shows the logic of the cloud-based cadastral monitoring workflow. The key feature of the scheme is the transition from satellite input data to diagnostic indicators and then to a validated classification output. This sequence makes it possible to move from visual

interpretation of images to a structured set of monitoring products that can support targeted verification of agricultural land condition.

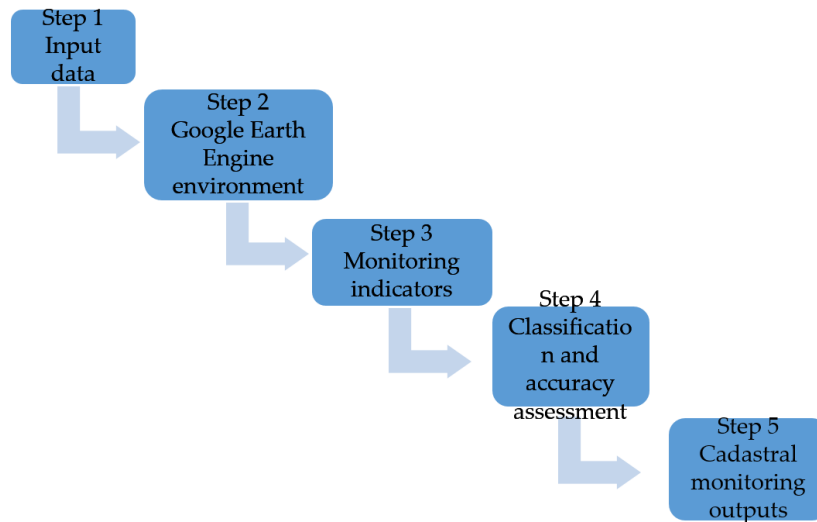


Figure 1. Scheme for using Google Earth Engine for cadastral monitoring of agricultural lands in Almaty Region

Note – compiled by the authors

Table 1. Input data and indicators used for cadastral monitoring in Google Earth Engine

Data / indicator	Source	Period	Role in the monitoring workflow
Administrative boundary of Almaty Region	User asset in Google Earth Engine / official or open geospatial data	Current boundary	Spatial frame for clipping, masking and exporting monitoring outputs
Landsat 8/9 Surface Reflectance	Google Earth Engine data catalog / USGS Landsat Collection 2 Level 2	2015, 2020, 2025	Multispectral basis for comparable seasonal composites and indices
Sentinel-2 imagery	Google Earth Engine data catalog / Copernicus Sentinel-2 mission	Auxiliary reference where applicable	Auxiliary visual reference for checking training samples
NDMI	Calculated from NIR and SWIR1 bands	2015, 2020, 2025	Indicator of moisture-related surface condition
BSI	Calculated from BLUE, RED, NIR and SWIR1 bands	2015, 2020, 2025	Indicator of exposed or weakly vegetated surface

Note – compiled by the authors

The main data source was Landsat 8/9 Surface Reflectance imagery available in the Google Earth Engine catalog. Landsat was selected because it provides comparable multispectral observations for 2015, 2020 and 2025 at regional scale. Sentinel-2 imagery was used as an auxiliary visual reference when interpreting training areas. This combination is appropriate for regional monitoring because it balances temporal comparability, spectral information and visual detail (Drusch et al., 2012; Phiri et al., 2020; Segarra et al., 2020; U.S. Geological Survey, 2019).

For each selected year, a seasonal composite was generated for the vegetation period. This procedure reduces the influence of single-date anomalies, cloud contamination and missing pixels. The processing steps included filtering by date and cloud cover, masking clouds and shadows, clipping to the regional boundary and adding calculated index bands. The same script-

based procedure was applied to all years in order to ensure comparability of the resulting layers (Gorelick et al., 2017; Google Developers, 2024).

Two spectral indicators were used for monitoring interpretation. NDMI was applied to characterize moisture-related differences in vegetation and soil cover. In cadastral diagnostics, this index is useful for identifying areas where surface moisture conditions and vegetation status may differ between observation years (Gao, 1996). The index formula is presented as follows:

$$\text{NDMI} = (\text{NIR} - \text{SWIR1}) / (\text{NIR} + \text{SWIR1})$$

BSI was applied to emphasize open or sparsely vegetated surfaces. In the context of cadastral monitoring, increased BSI values may indicate bare soil, temporarily exposed cropland, weak vegetation cover, construction-related disturbance or other changes in actual land use. Therefore, BSI was interpreted together with NDMI and not as an isolated indicator (Rikimaru et al., 2002). The BSI formula is presented as follows:

$$\text{BSI} = ((\text{SWIR1} + \text{RED}) - (\text{NIR} + \text{BLUE})) / ((\text{SWIR1} + \text{RED}) + (\text{NIR} + \text{BLUE}))$$

For the final 2025 monitoring slice, the Random Forest classifier was trained using the spectral bands BLUE, GREEN, RED, NIR, SWIR1 and SWIR2 together with NDMI and BSI. Four monitoring classes were used: stable vegetation cover, open or sparsely covered soil, water bodies, and built-up or non-agricultural areas. The training and validation procedure is presented in Figure 2.

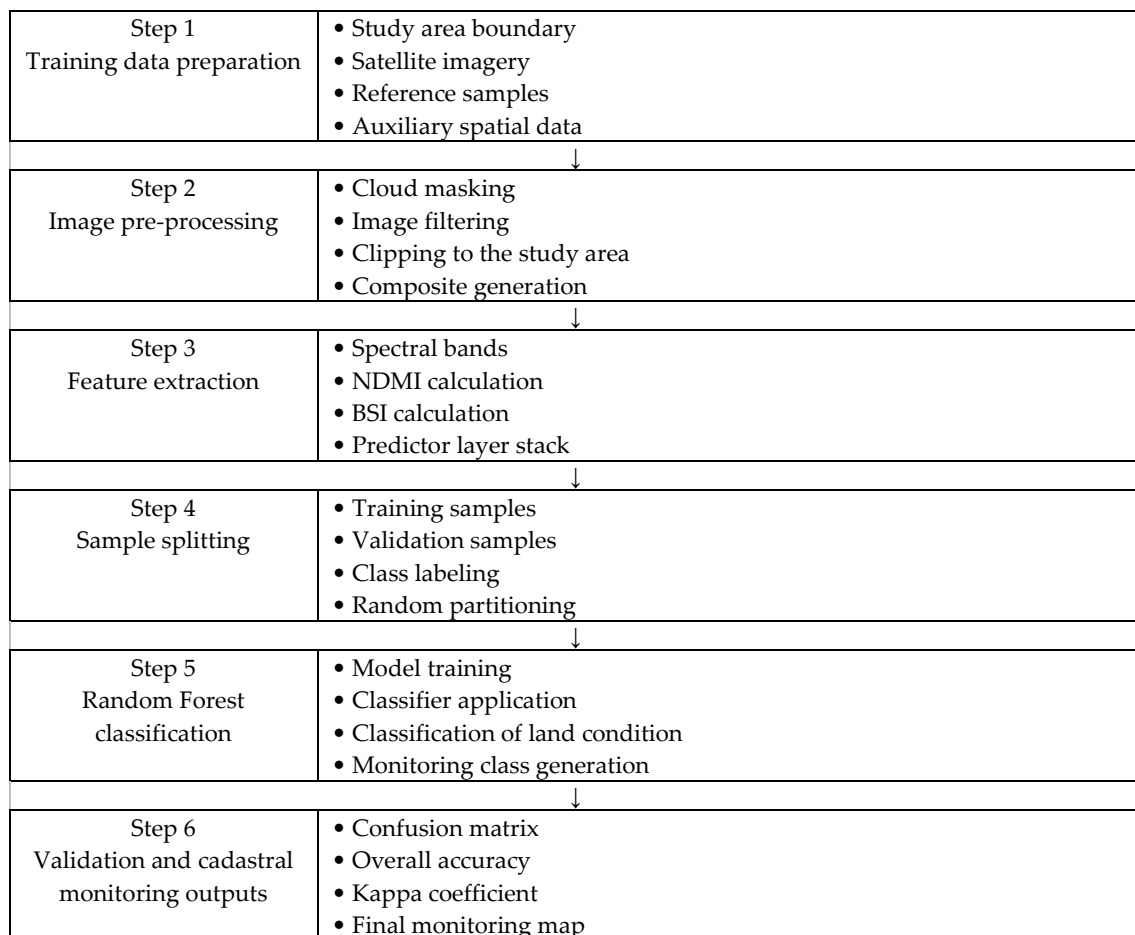


Figure 2. Workflow of Random Forest training and validation used for cadastral monitoring of agricultural lands in Almaty Region.

Note – compiled by the authors

Figure 2 details the classification stage of the workflow. The model was not treated as a purely automatic procedure: reference samples were first prepared, labelled and checked against satellite images and auxiliary layers. The sample set was then divided into training and validation parts so that classification accuracy could be evaluated independently from the data used for model training. This separation is important for using the resulting map as a reliable diagnostic product rather than only as a visual classification output (Breiman, 2001; Belgiu & Dragut, 2016).

Accuracy assessment was carried out using a validation sample and standard classification metrics. The confusion matrix was used to identify class-level agreement and possible spectral mixing between classes. Overall accuracy and the Kappa coefficient summarize the general reliability of the classification, while producer and consumer accuracies indicate which classes are more stable and which require more cautious interpretation (Cohen, 1960; Congalton, 1991; Foody, 2002; Olofsson et al., 2014; Google Developers, 2024).

RESULTS AND DISCUSSION

The results are organized according to the logic of the satellite-based cadastral monitoring workflow. First, the temporal behaviour of NDMI is considered as an indicator of moisture-related surface conditions. Second, BSI is examined to identify exposed or weakly covered surfaces. Third, both the spectral bands and the derived indices are combined in the Random Forest classification to produce the final map of monitoring classes. This sequence allows the interpretation to move from separate remote sensing indicators to an integrated classification result that can be used for preliminary cadastral diagnostics. Accordingly, the temporal dynamics shown in Figures 3 and 4 cover 2015, 2020 and 2025, whereas Figure 5 and the class-area statistics in Table 3 characterize 2025 only.

The NDMI maps for 2015, 2020 and 2025 show that moisture-related conditions are unevenly distributed within Almaty Region. Higher NDMI values are mainly associated with water-influenced areas, irrigated agricultural zones, river valleys and mountain or foothill territories with more persistent vegetation cover. These areas are important for cadastral monitoring because they may indicate zones of stable vegetation development and relatively favorable moisture conditions during the selected observation period.

Lower NDMI values are more typical for drier surfaces, sparsely vegetated areas and territories where the vegetation signal is weak. Such areas may include arid plains, temporarily bare agricultural fields, degraded surfaces or land parcels where vegetation cover is reduced during the growing season. Therefore, NDMI should not be interpreted as a direct cadastral category, but rather as a diagnostic indicator that helps identify spatial differences in the moisture-related condition of land cover.

The comparative interpretation of NDMI for three observation years makes it possible to identify both relatively stable areas and zones where moisture-related conditions changed over time. For cadastral monitoring, this is useful because repeated decreases in NDMI may indicate territories that require additional verification using cadastral boundaries, field observations or other auxiliary data. At the same time, the index values should be interpreted carefully, since they may be influenced by seasonal differences, crop rotation, irrigation practices and the date of satellite image acquisition.

The use of the same visualization range and colour scale for 2015, 2020 and 2025 ensures that the maps can be compared consistently. This is especially important when NDMI is used not as a single-year descriptive layer, but as part of a monitoring workflow aimed at detecting spatial patterns and potential changes in agricultural land condition (Gao, 1996; Segarra et al., 2020). The resulting NDMI maps are presented in Figure 3.

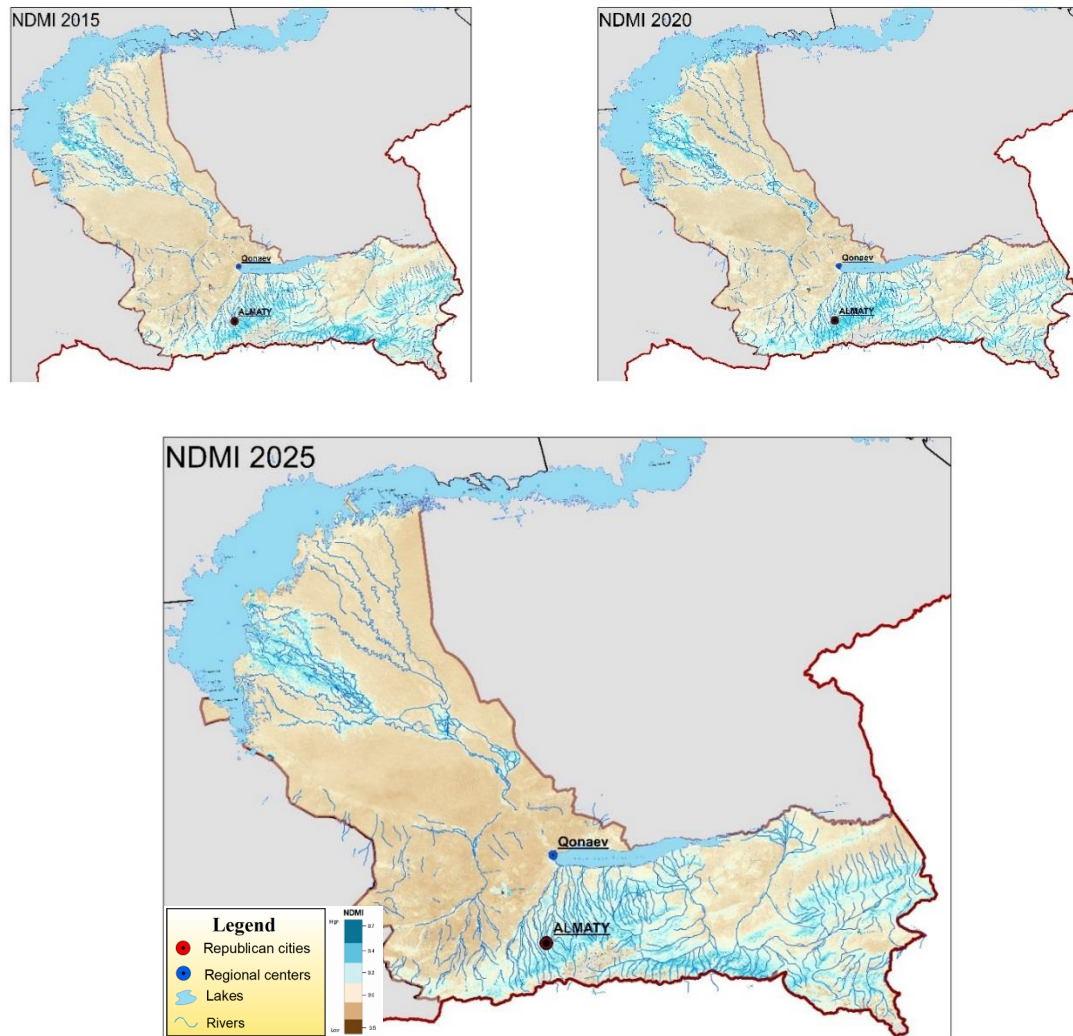


Figure 3. Dynamics of NDMI in Almaty Region in 2015, 2020 and 2025

Note – compiled by the authors

Figure 3 should be read as a temporal diagnostic indicator. It does not replace cadastral information, but it helps identify zones where moisture-related conditions may have changed and where further comparison with cadastral parcels, agricultural records or field observations may be justified. In this way, NDMI supports the first stage of screening before more detailed cadastral verification is carried out.

BSI provides a different diagnostic signal. While NDMI emphasizes moisture and vegetation condition, BSI highlights open, sparsely covered or disturbed surfaces. Areas with relatively high BSI values may correspond to bare agricultural fields, dry soil surfaces, degraded vegetation cover or non-agricultural disturbance. For cadastral interpretation, the index is most informative when it is analysed together with NDMI and the final classification map (Rikimaru et al., 2002; Maxwell et al., 2018).

Figure 4 complements the NDMI analysis by showing where exposed surface conditions are most clearly expressed. If a territory demonstrates both lower NDMI and higher BSI, it can be selected for closer inspection. However, such a signal should not be interpreted mechanically, because crop calendar, irrigation regime, temporary tillage, soil background and settlement expansion may produce similar spectral responses.

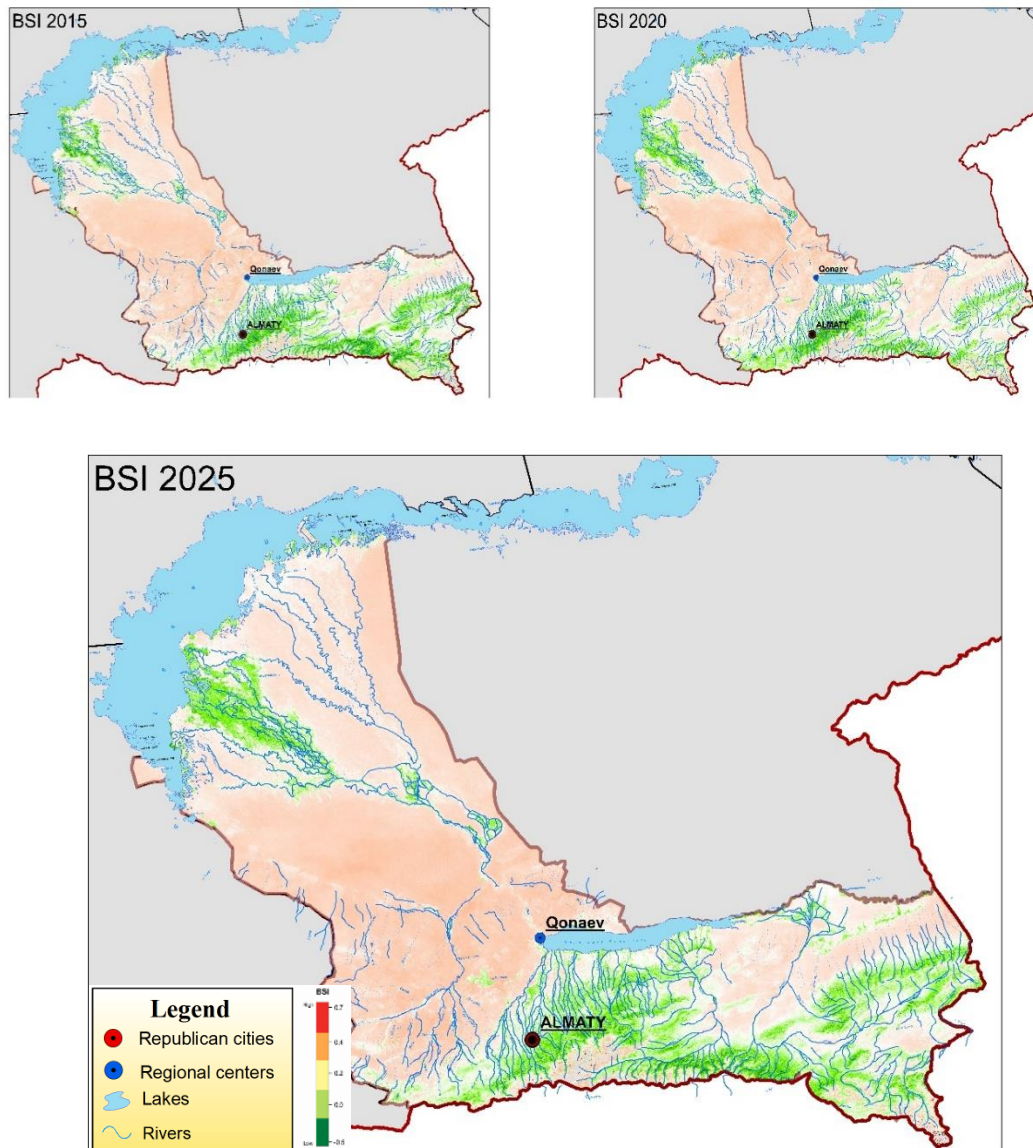


Figure 4. Dynamics of BSI in Almaty Region in 2015, 2020 and 2025

Note – compiled by the authors

The final stage of the analysis was supervised classification using Random Forest. The classifier integrated the original spectral bands with NDMI and BSI and assigned each pixel to one of four monitoring classes. This result is intended to summarize several remote-sensing characteristics in a single map that is easier to compare with cadastral boundaries, administrative units and verification priorities (Breiman, 2001; Belgiu & Dragut, 2016; Maxwell et al., 2018).

Figure 5 represents the main operational output of the study for the 2025 observation period. The 2015 and 2020 datasets are used for temporal comparison of NDMI and BSI, whereas the Random Forest map shown here characterizes the most recent 2025 monitoring slice. Compared with separate NDMI and BSI maps, the classification map provides a generalized view of agricultural land condition and separates vegetation-dominated areas, exposed soil, water bodies and built-up or non-agricultural territories. The map should be used as a diagnostic layer for planning cadastral checks and not as an official cadastral document.

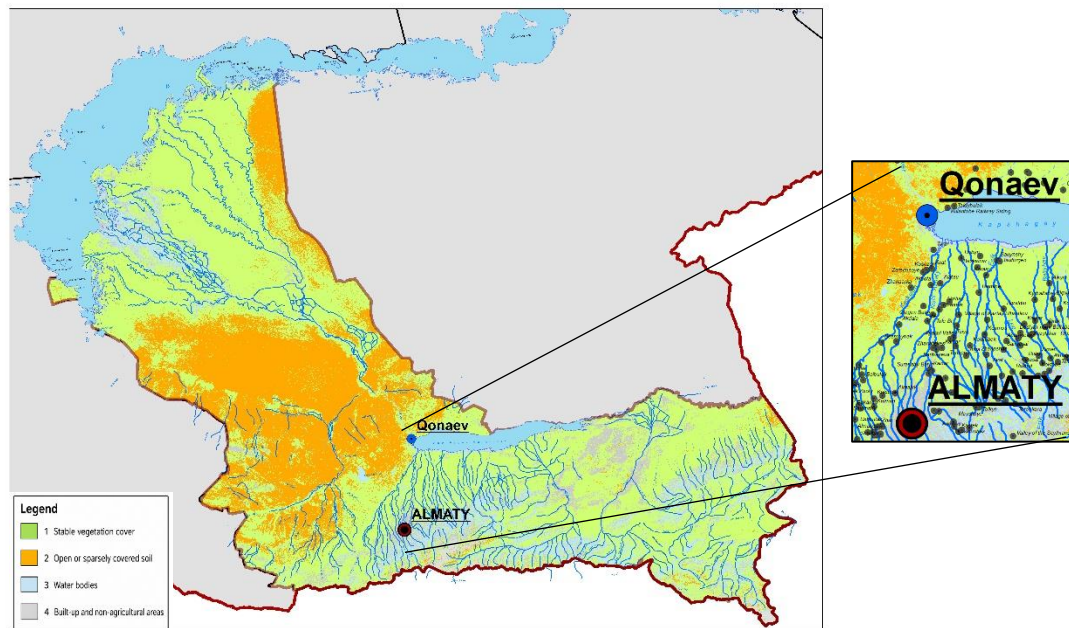


Figure 5. Monitoring classes of agricultural land condition for 2025 obtained using Random Forest in Google Earth Engine

Note – compiled by the authors

In the context of cadastral monitoring, the most important value of Figure 5 is that it converts spectral differences into clearly interpretable monitoring classes. This makes it easier to compare the classification result with administrative boundaries, rural districts, cadastral parcels and field verification materials. Areas classified as open or sparsely covered soil may require particular attention, especially where they are located within agricultural zones and coincide with reduced vegetation or moisture indicators.

The reliability of the 2025 classification was evaluated using validation results generated in Google Earth Engine. The assessment included the confusion matrix, overall accuracy, Kappa coefficient, producer accuracy and consumer accuracy. These metrics are summarized in Table 2 and provide a basis for judging whether the classification output is sufficiently stable for preliminary monitoring purposes.

Table 2. Accuracy assessment of the 2025 Random Forest classification results in Google Earth Engine

Metric	Meaning	GEE function	Result
Confusion matrix	Distribution of reference and classified samples by classes	errorMatrix()	Generated in GEE; summary metrics below
Overall accuracy	Share of correctly classified validation samples	accuracy()	95.16%
Kappa coefficient	Agreement coefficient corrected for random agreement	kappa()	0.841
Producer accuracy	Accuracy by reference class	producersAccuracy()	92.11%
Consumer accuracy	Accuracy by mapped class	consumersAccuracy()	81.13%

Note – compiled by the authors

Table 2 indicates that the 2025 Random Forest classification achieved a high overall accuracy of 95.16% and a Kappa coefficient of 0.841. These values show that the model can distinguish the selected monitoring classes with acceptable reliability. At the same time, the producer and consumer accuracy values should be interpreted at the class level, especially for classes that may have similar spectral behaviour, such as exposed soil and built-up areas (Cohen, 1960; Congalton, 1991; Foody, 2002).

In addition to classification accuracy, the area of each monitoring class was calculated from the 2025 classified raster. Class areas help translate the map into quantitative indicators that are more convenient for cadastral interpretation. The area statistics were derived from the classified raster using the pixel count of each class and the spatial resolution of the Landsat grid. The results are presented in Table 3.

Table 3. Area of monitoring classes according to the 2025 Random Forest classification results

№	Monitoring class	Area, ha	Share, %
1	Stable vegetation cover	8,328,189.15	58.50
2	Open or sparsely covered soil	3,255,803.37	22.87
3	Water bodies	1,510,826.40	10.61
4	Built-up and non-agricultural areas	1,140,726.60	8.01
Total	Total classified area	14,235,545.52	100.00
<i>Note – compiled by the authors</i>			

Table 3 shows that the largest share of the classified territory corresponds to stable vegetation cover, while open or sparsely covered soil forms the second largest class. Water bodies and built-up or non-agricultural areas occupy smaller shares. These proportions should be interpreted as results of the 2025 monitoring classification, not as official cadastral land-category statistics. Nevertheless, they provide a useful quantitative basis for identifying areas where additional verification may be prioritized.

Overall, the study demonstrates a stepwise approach in which NDMI, BSI and Random Forest classification perform different roles. NDMI supports the interpretation of moisture-related changes, BSI highlights exposed surfaces, and Random Forest integrates several predictors into an operational classification map. Such a structure makes the workflow suitable for repeated cadastral screening of agricultural territories. Thus, the 2015–2025 temporal component is represented by NDMI and BSI dynamics, while the classification statistics provide a detailed snapshot for 2025.

CONCLUSION

This study proposed a cloud-based workflow for preliminary cadastral monitoring of agricultural lands in Almaty Region using Google Earth Engine and Random Forest. The method combines seasonal Landsat composites, spectral indicators and supervised classification to produce a diagnostic map of land-condition classes.

NDMI and BSI provided complementary information. NDMI was used to interpret moisture-related differences, whereas BSI helped identify open or sparsely covered surfaces. Their joint use made it possible to move beyond single-index interpretation and to provide a more structured basis for cadastral screening.

The 2025 Random Forest classification transformed spectral bands and calculated indices into four monitoring classes: stable vegetation cover, open or sparsely covered soil, water bodies, and built-up or non-agricultural areas. The validation results indicate that the classification can be used as a preliminary analytical layer for identifying territories that require additional cadastral or field verification.

Future work should focus on linking the classified raster with parcel-level cadastral boundaries, improving reference samples through field observations and applying the workflow to regular monitoring periods. The proposed approach is especially useful as an auxiliary diagnostic tool for land-use control, because it provides reproducible spatial evidence before detailed administrative or field-based verification.

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INFORMED CONSENT STATEMENT: Not applicable.

DATA AVAILABILITY STATEMENT: The satellite data used in the study are available through Google Earth Engine. The processed monitoring layers and classification outputs can be provided by the authors upon reasonable request.

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DISCLOSURE OF THE USE OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES: Artificial intelligence tools were used for language polishing and formatting assistance only. All methodological decisions, data interpretation and final conclusions were checked and approved by the authors.

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