The role of remote sensing data in providing land monitoring information

Ainura Batykova[1,1], *Beksultan* Tuleev[2], *Tamchybek* Tuleev[1], *Sobir* Ruziboev[3], *Azim* Gofirov[4], *Kuatbay* Ismaylov[5], *Albina* Valiyeva[3]

[1]Kyrgyz National Agrarian University named after K.I. Skryabin, Bishkek, Kyrgyz Republic
[2] University of Trento,Via Sommarive, 9, 38123 Povo, Trento TN, Italy
[3] "TIIAME" National Research University, Tashkent, Uzbekistan
[4]Tashkent State Agrarian University Tashkent, Uzbekistan
[5]Karakalpak State University, Nukus city, Uzbekistan

Abstract. Over the past three decades, remote sensing technologies have become increasingly valuable for monitoring sustainable land management practices. Remote sensing allows for easy and versatile monitoring through various types of imagery, enabling land planners and managers to make well-informed decisions. This article explores key aspects of using Earth Remote Sensing (ERS) tools, particularly for tracking changes in forested areas. By leveraging satellite-derived time-series imagery, it is possible to monitor large regions continuously, assess forest conditions, and evaluate the impact of various natural and human-induced factors over time. This study presents an analysis of forest changes over a specific period, providing insights into the dynamics and health of these ecosystems.

1 Introduction

Land monitoring is the process of keeping an eye on effective land usage, land control, and land conservation in general. Following state approval, a single system is used for land monitoring, land reclamation processes, and land management kinds and techniques. Land monitoring serves as the foundation for the state's control over the intentional and prudent use of land resources, the upkeep of the state land cadastre, land usage, land management, and information assistance for land preservation organizations.

The following subsystems are separated into the land fund based on classifications, and monitoring is done with the goal of land usage in mind: monitoring lands used for agriculture, settlements, industry, transportation, communications, defense, and other uses; monitoring lands used for recreation, rehabilitation, and nature preservation; monitoring lands used for historical and cultural purposes; monitoring lands used for forests; monitoring lands used for water fund purposes; monitoring lands used for reserve purposes.

A thorough approach to study and database creation is necessary for the Kyrgyz Republic's (KR) land management and resource rationalization. Effective land management is nearly impossible without an information database. Stated differently, the implementation

1 Corresponding author: nargizaeshmurodova0306@gmail.com

of contemporary technologies and applications in data collecting and analysis is necessary to address many issues pertaining to research, management, and production. It is described in KR's Land Law. [1] that monitoring of lands is a system of constant monitoring of the current state of land funds for timely detection of changes, its evaluation, warning, and resolving negative issues. With the right hardware and software, modern computer systems can process large amounts of data accurately and efficiently. GIS and Earth Remote Sensing (ERS) are examples of useful software and IT decisions used in land management and governmental land cadastre [2]. Web-based mapping and distributed systems for measurement, planning, and automation are two examples of how several scientific domains converge to generate geographic information systems [3]. Depending on its intended use, a GIS may integrate open map data and technical methods with operational, cadastral, environmental, and other data. Due to the extremely accurate coordinate computations that are essential in several scientific domains, ERS gained a lot of popularity. By using satellite-derived time-series photos, the whole region may be regularly monitored. [4–6], the current state of woods, and its evaluation due to different changing factors over time either natural or artificial [7–10]. It is crucial to have a monitoring system of vegetation coverage because it is a pivotal factor in landscape ecology studies [11–14]. These days, specialized processing techniques for satellite-obtained photos are employed to monitor lands or address the majority of associated issues. The Normalized Difference Vegetation Index (NDVI) is the most often used index in spectral study of vegetation. [15–18].

The primary objective of this study is to evaluate the effectiveness of satellite-based remote sensing for land monitoring, focusing on how time-series data like NDVI can provide accurate insights into land use, management practices, and environmental changes. The study aims to establish a practical framework for monitoring shifts in land cover, assessing vegetation health, and understanding the impact of both natural and human activities on land degradation. By analyzing patterns like deforestation and urban development, the research highlights how remote sensing supports sustainable land management and conservation planning in the Kyrgyz Republic. Additionally, the study will provide recommendations for integrating remote sensing into land monitoring, considering practical constraints and proposing efficient use of geospatial data to support informed, data-driven decision-making.

2 Methodology

This research aims to identify and analyze changes in vegetation within the Chui region, focusing specifically on the Issyk-Atinsk district. The study area is defined by geographic coordinates ranging from 42°52'25.36"N, 75°9'31.31"E (starting point) to 42°49'43.65"N, 75°16'42.56"E (ending point). This geographic framework situates the research within a diverse ecological landscape, providing a basis for examining the dynamics of vegetation change in response to both environmental factors and human activities.

This research utilizes high-resolution satellite imagery from the Landsat 4-5 Thematic Mapper (TM) and the Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) as the foundational data sources for evaluating vegetation dynamics in the Chui region, specifically within the Issyk-Atinsk district.

For the historical analysis covering the period from 2010 to 2011, a total of X cloud-free Landsat 4-5 TM images were systematically selected. These images serve as baseline data for understanding historical vegetation conditions within the study area. The selection process prioritized images taken at similar times during the year to mitigate seasonal variability. Landsat 8 OLI/TIRS: The analysis of more recent vegetation conditions, spanning the years 2016 to 2019, involved the selection of Y cloud-free images. Similar to the Landsat 4-5 dataset, images were selected to represent each season (spring, summer, fall, winter) where feasible [19]. This selection methodology enhances the temporal resolution and ensures comprehensive coverage of seasonal growth patterns and disturbances. Temporal Resolution: The images chosen were intended to reflect key seasonal growth phases. This seasonal approach provides insights into variations in vegetation phenology, thereby enabling a robust comparison between historical and contemporary vegetation states.

To ensure the reliability and accuracy of the analysis across varying time periods and sensor types, a rigorous preprocessing workflow was implemented, as illustrated in Figure 1.

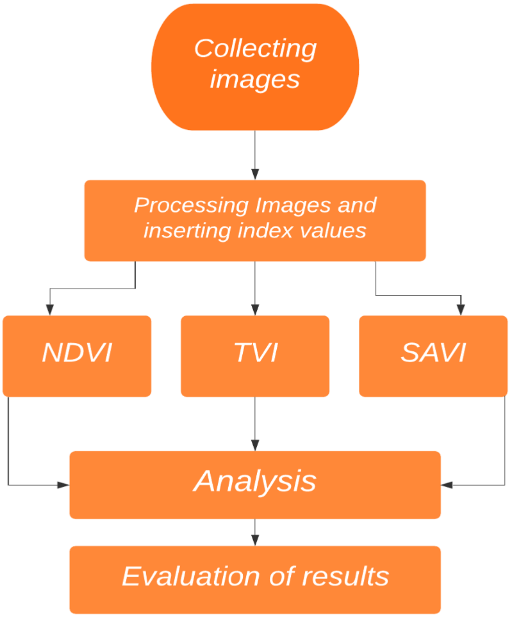

Fig. 1. Flowchart of using methodology

To minimize atmospheric interference and achieve accurate surface reflectance values, the Dark Object Subtraction (DOS) method was employed. This correction method enhances the reliability of reflectance values utilized for vegetation indices, ensuring more precise NDVI assessments. The Fmask algorithm was implemented to effectively identify and mask cloud and shadow pixels. This algorithm analyzes brightness, temperature, and spectral characteristics to accurately delineate cloud cover, ensuring that only clear pixels contribute to the NDVI calculations. Exclusion of these masked pixels is crucial to prevent distortions in vegetation index assessments.

All images were geometrically corrected and aligned to a common coordinate system using Ground Control Points (GCPs). This correction is vital for eliminating spatial misalignments and distortions, which is especially significant when comparing multi-temporal data from different sensors. Radiometric calibration was performed to convert digital numbers (DNs) to top-of-atmosphere reflectance values. This process ensures that the reflectance data from Landsat 4-5 and Landsat 8 are comparable, facilitating accurate longitudinal analysis.

The Normalized Difference Vegetation Index (NDVI) was selected as the primary index for evaluating vegetation changes due to its simplicity and widespread use in similar research studies. NDVI's popularity stems from its effective ability to provide a quick assessment of vegetation health by measuring the difference in reflectance between red and near-infrared light. However, NDVI does have some limitations. It can struggle to capture changes in areas with dense vegetation, where saturation may occur, making it challenging to detect subtle

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variations in vegetation cover and health [14]. Additionally, soil background can introduce "noise" into NDVI results, potentially skewing assessments in regions with sparse vegetation or exposed soil.

To address these limitations, the study also incorporates alternative vegetation indices. The Soil Adjusted Vegetation Index (SAVI), for example, includes a soil brightness correction factor to reduce soil-related noise, making it more reliable in areas where vegetation is sparse or where soil exposure might interfere with readings. Additionally, the Triangular Vegetation Index (TVI), which considers specific spectral features to assess vegetation cover, will be reviewed and compared with NDVI. By examining SAVI and TVI alongside NDVI, the study aims to obtain a more comprehensive understanding of vegetation patterns and health across varying landscape conditions [6, 20, 21].

NDVI is a valuable tool for quantitatively assessing vegetation cover and health. By measuring vegetation reflectance in the red and near-infrared regions of the electromagnetic spectrum, NDVI provides insights into the green biomass present in an area. This information is particularly important in identifying vegetation stress or degradation, allowing for targeted interventions and efficient land management. In cases where vegetation is in poor condition, NDVI-based analysis can guide the development of effective solutions to improve plant health and optimize land usage.

In this study area, approximately 20 million hectares make up the land fund of the state, with protected natural areas covering 6.1% of this total. NDVI helps to assess the current state of vegetation within these lands, offering an indicator of both density and quality. For agricultural applications, NDVI is instrumental in evaluating the density of vegetation, assessing plant germination, monitoring growth stages, and ultimately evaluating the efficiency of land use. This allows growers and land managers to make informed decisions regarding crop health and resource allocation.

The formula for calculating NDVI is as follows:

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

where:

NIR represents the reflectance in the near-infrared spectrum, which is strongly reflected by healthy vegetation.

RED represents the reflectance in the red spectrum, which is absorbed by chlorophyll in green plants.

This calculation yields values between -1 and +1, with higher positive values indicating healthier and denser vegetation, while lower or negative values suggest bare soil, water, or vegetation stress [23].

The Soil Adjusted Vegetation Index (SAVI) is another useful spectral index that enhances the sensitivity of vegetation analysis in areas with significant soil background. Developed to account for the influence of soil brightness on vegetation reflectance, SAVI incorporates a correction factor, L, to minimize soil effects. The formula for calculating SAVI is given by:

$$SAVI = \frac{NIR - RED}{NIR + RED + L} * (1 + L) \tag{2}$$

Where:

NIR is the brightness of the object in the near-infrared wavelength,

RED is the brightness of the object in the red wavelength,

L is the soil adjustment factor, which typically ranges from 0 to 1. A common choice for L is 0.5, particularly in regions with varying vegetation density.

SAVI is particularly effective in areas where vegetation density is low and soil exposure is high, making it a valuable complement to NDVI.

The Triangular Vegetation Index (TVI) is another index utilized to assess vegetation conditions. TVI provides a linear approximation of vegetation cover by measuring the difference between the near-infrared and green reflectance values. The formula for calculating TVI is:

$$TVI = 60(NIR - GREEN) - 200(RED - GREEN) \quad (2)$$

NIR is the brightness of the object in the near-infrared wavelength,
GREEN is the brightness of the object in the green wavelength.

TVI is advantageous in that it can capture variations in vegetation density and health while being less sensitive to soil and atmospheric effects compared to NDVI. Both SAVI and TVI serve as important tools alongside NDVI for a comprehensive evaluation of vegetation status, especially in diverse landscapes.

3 Results and discussion

The analysis of satellite images using NDVI, SAVI, and TVI indices has shown clear changes in the vegetative status of the selected natural reserve area over time. The classification based on NDVI values allowed us to categorize the landscape types, as presented in Table 1. The classification revealed that the overall vegetation coverage with NDVI values higher than 0.5 (including shrublands, woodlands, and other higher vegetation types) has decreased significantly, reaching a minimum of 30 hectares in 2016. This trend is visually represented in Figure 2, which illustrates the total area in hectares with NDVI values above 0.5.

Table 1. Index classification table

NDVI value	Landscape type
0.8-1	Tropical and subtropical moist forest (TSMF)
0.67-0.8	Woodlands
0.4-05	Shrublands and alike vegetation
0.2-0.4	Grasslands
0.1-0.2	Soil
-0.42 - (-0.33)	Area filled with water
-0.55 - (-0.5)	Concrete and bitumen

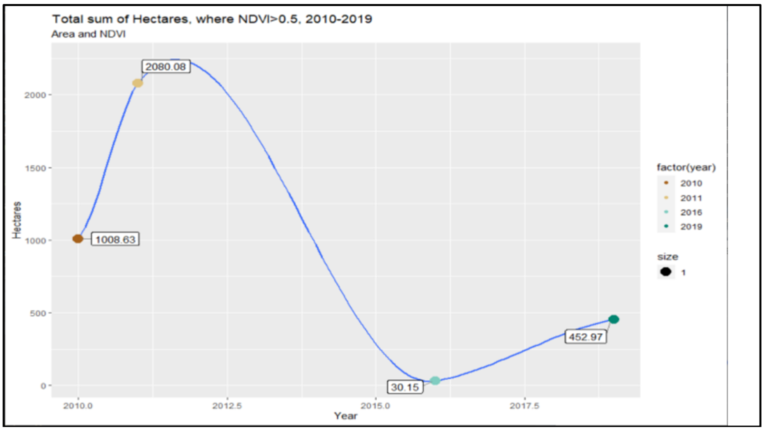

Fig. 2. Total sum of Hectares with NDVI >0.5.

Scatterplots detailing the distribution of NDVI values for each year can be found in Appendix 1 (Figures 3-5). Notably, 2011 recorded higher-than-average precipitation levels, as indicated by the FAO report [19], which likely contributed to the high vegetation coverage observed that year. Conversely, 2015 was reported as the hottest year on record, according to NASA's observatory report [20], which may account for the reduced vegetation coverage in the following years (Figures 4-7).

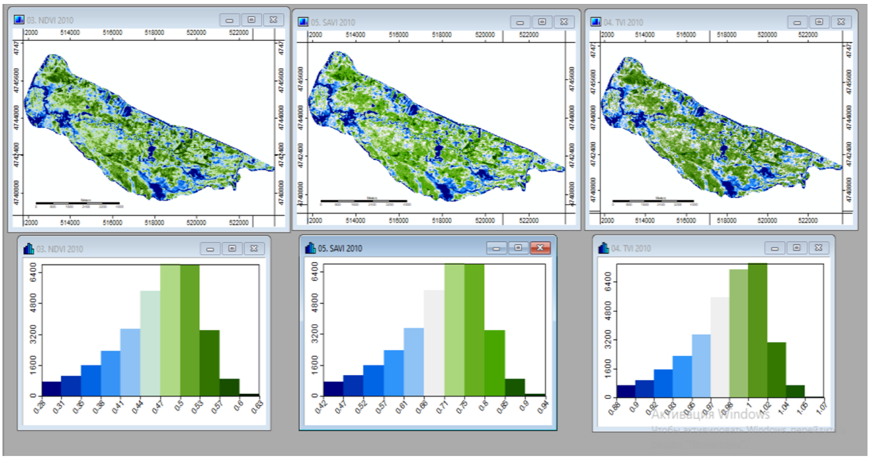

Fig. 3. NDVI, SAVI, TVI, 2010

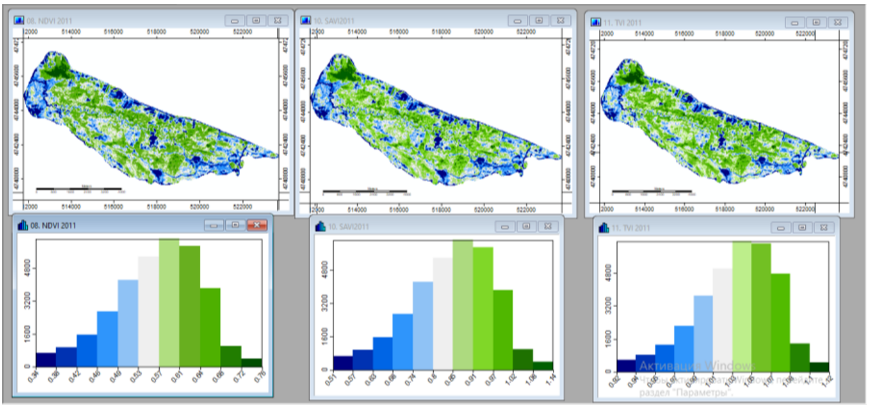

Fig. 4. NDVI, SAVI, TVI 2011

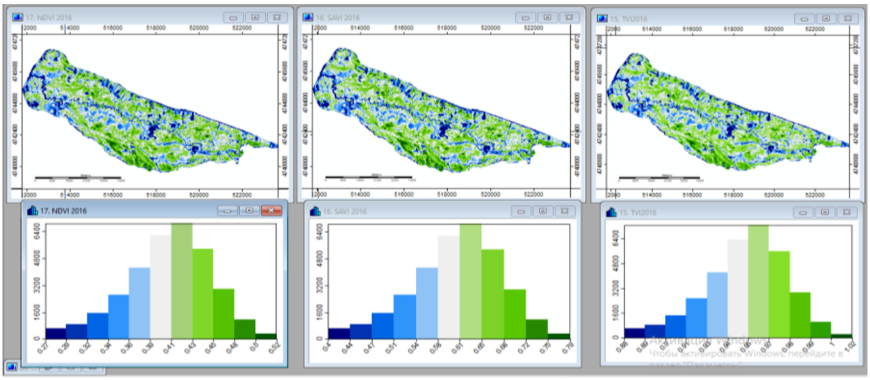

Fig. 5 NDVI, SAVI, TVI 2016

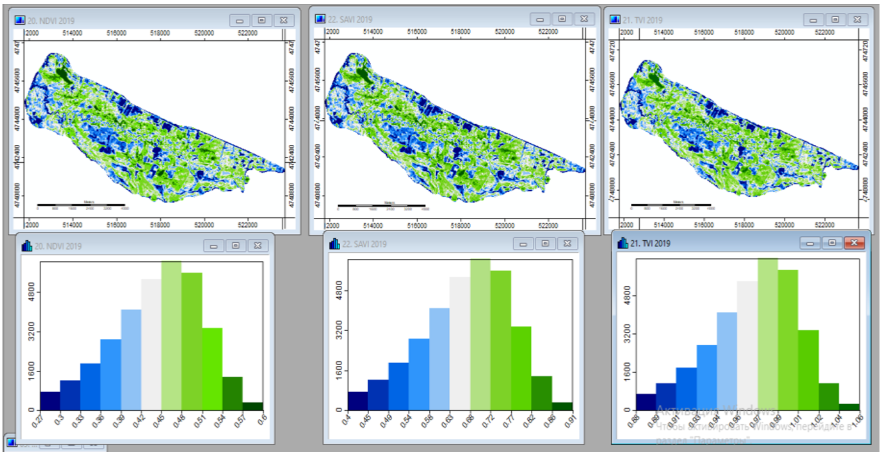

Fig. 6 NDVI, SAVI, TVI 2019

In addition, the SAVI index proved particularly useful for delineating areas with lower vegetation cover (below 40%), as it effectively captured the boundaries of woodland areas. Among the indices, NDVI showed the most significant changes across different years, highlighting its sensitivity to shifts in vegetation density and health.

The findings emphasize the importance of remote sensing data in land management and decision-making processes. Remote sensing technology provides a valuable tool for tracking changes in vegetation and land composition, enabling land managers to make informed decisions. Real-time monitoring and assessment of these changes are essential for optimizing land use, especially at local levels such as cities and districts.

4 Conclusion

In conclusion, satellite imagery and remote sensing data are invaluable tools for environmental assessment and land monitoring. This study underscores the importance of using such data to track vegetation changes over time and to understand the environmental factors driving these variations. Accurate monitoring of vegetation dynamics is crucial for effective land management and conservation efforts in natural reserves and similar ecosystems.

The scatterplots in Figures 3 and 5 visually depict the distribution of vegetation in relation to NDVI values over time, highlighting notable changes in vegetation cover. Historical climate data supports the findings by illustrating how environmental factors influences vegetation. For instance, the FAO's report indicates that the unusually high precipitation in 2011 likely contributed to the observed increase in vegetation. Conversely, the extreme heat recorded by NASA in 2015 likely resulted in reduced vegetation cover for that year.

This analysis reaffirms the role of remote sensing as a critical tool in environmental management, enabling timely and informed decisions to enhance land use and conservation practices.

References

1. A. Batykova, T. Tuleev, B. Tuleev, A. Asanaliev, V. Denisov, S. Hegay, V. Sultanbaeva, and A. Babajanov, E3S Web Conf. **386**, 05001 (2023)

2. A. Batykova, T. Tuleev, B. Tuleev, A. Asanaliev, V. Denisov, S. Hegay, V. Sultanbaeva, and A. Babajanov, E3S Web of Conferences **386**, (2023)
3. A. Varlamov, S. Galchenko, D. Antropov, R. Kirillov, and A. Fomina, IOP Conference Series: Earth and Environmental Science **867**, 012163 (2021)
4. Z. Gu, Z. Zeng, X. Shi, D. Yu, W. Zheng, Z. Zhang, and Z. Hu, Frontiers of Forestry in China **4**, 402 (2009)
5. Gao, Y. Vegetation Coverage change and its influencing factors in the Mu Us Sandy Land from 2000 to 2015. (2020).
6. G. Azzari and D. B. Lobell, Remote Sensing of Environment **202**, 64 (2017)
7. H. Huang, Y. Chen, N. Clinton, J. Wang, X. Wang, C. Liu, P. Gong, J. Yang, Y. Bai, Y. Zheng, and Z. Zhu, Remote Sensing of Environment **202**, 166 (2017)
8. I. Aslanov, N. Teshaev, K. Khayitov, U. Mukhtorov, J. Khaitbaeva, and D. Murodova, E3S Web of Conf. **443**, 06015 (2023)
9. I. Aslanov, I. Jumaniyazov, N. Embergenov, K. Allanazarov, G. Khodjaeva, A. Joldasov, and S. Alimova, in *XV International Scientific Conference "INTERAGROMASH 2022,"* edited by A. Beskopylny, M. Shamtsyan, and V. Artiukh (Springer International Publishing, Cham, 2023), pp. 1899–1907
10. M. Usman, R. Liedl, M. A. Shahid, and A. Abbas, *Land Use/Land Cover Classification and Its Change Detection Using Multi-Temporal MODIS NDVI Data* (Science in China Press, 2015), pp. 1479–1506
11. A. H. E. Nahry, R. R. Ali, and A. A. E. Baroudy, *An Approach for Precision Farming under Pivot Irrigation System Using Remote Sensing and GIS Techniques* (Elsevier B.V., 2011), pp. 517–531
12. J. Garcia, A. Barbedo, L. Alvim, S. Romani, R. Ribeiro, and V. Gonçalves, *A Review on the Automatic Segmentation and Classification of Agricultural Areas in Remotely Sensed Images* (2018), p. 156
13. M. K. Kolli, C. Opp, D. Karthe, and M. Groll, Water (Switzerland) **12**, 1 (2020)
14. O. Dubovyk, G. Menz, A. Lee, J. Schellberg, F. Thonfeld, and A. Khamzina, *SPOT-Based Sub-Field Level Monitoring of Vegetation Cover Dynamics: A Case of Irrigated Croplands* (2015), pp. 6763–6783
15. W. Wu, *The Generalized Difference Vegetation Index (GDVI) for Dryland Characterization* (2014), pp. 1211–1233
16. C. Conrad, S. W. Dech, M. Hafeez, J. Lamers, C. Martius, and G. Strunz, *Mapping and Assessing Water Use in a Central Asian Irrigation System by Utilizing MODIS Remote Sensing Products* (2007), pp. 197–218
17. M. Langford and D. J. Unwin, Cartographic Journal **31**, 21 (1994)
18. M. Rahman, A. Islam, and M. Hassan, *Change Detection of Winter Crop Coverage and the Use of LANDSAT Data with GIS | Shareful Hassan - Academia.Edu* (2005), pp. 1–13
19. A. Bannari, D. Morin, F. Bonn, and A. R. Huete, Remote Sensing Reviews **13**, 95 (1995)
20. W. G. Alemu and G. M. Henebry, Remote Sensing **8**, 1 (2016)
21. K. Lee, K. Kim, S.-G. Lee, and Y. Kim, ISPRS International Journal of Geo-Information **9**, 257 (2020)