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Monitoring and mapping of desertification process using geospatial data and GIS technologies in Mirzachul area

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Abstract. Desertification reduces the land's ability to withstand changes in climate, including the availability of water and other resources. Remote sensing technology has the potential to monitor and assess land degradation over time. The aim of this study is to use remote sensing images to assess desertification in Uzbekistan and compare the results with formal land productivity monitoring. The Mirzachul area was selected as a case study for monitoring desertification. Landsat images from 1994 to 2024 and the Soil Map of Uzbekistan were used as secondary data to determine the types of soil present in the case study area. The analysis focused on NDVI, SAVI, and WDVI. The results showed a significant difference in sandy bare soil and steppe trends in 1994, with approximately 4.5 million hectares of sandy bare soil and 250,000 hectares of steppe. However, by 2024, the area of sandy bare soil had decreased sharply by about 50% to 1.5 million hectares, while the area of steppe had increased to 2 million hectares.

1 Introduction

Desertification, the process of land degradation in arid and dry regions, presents significant challenges for the global environment, society, and economy. In the Mirzachul area of Central Asia, desertification poses a threat to the sustainability of ecosystems, water resources, and livelihoods [1]. The use of geospatial data and Geographic Information Systems (GIS) technologies for monitoring and mapping desertification processes has become essential for understanding landscape dynamics, assessing environmental change, and informing strategies for sustainable land management. This literature review examines the current state of research on desertification monitoring and mapping in the Mirzachul area, focusing on methodologies, findings, and challenges [2].

Desertification arises from human-induced land degradation in arid and dry regions, which account for 39.7% of the global terrestrial area, or 5.2 billion hectares out of a total of 13 billion hectares. Africa, Asia, and Australia have the highest concentration of dry

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territories worldwide. Desertification typically results from the overexploitation of land resources beyond their carrying capacity [3–5].

According to the UNCCD Fact Sheet (2015), desertification reduces the land's ability to withstand natural climate variability. This means that the soil, canopy cover, water supply, and other dryland resources are less resilient and struggle to recover from climatic disturbances such as drought. Land degradation significantly weakens this resilience, resulting in physical and socio-economic consequences. Additionally, soil fertility decreases, contributing to famine [6]. Over 85 percent of Uzbekistan's territory is composed of desert or semi-desert. Assessing the economic costs of land degradation in Uzbekistan requires consideration at three levels: field level, national level, and global level. At the field level, declining productivity is the main concern [7,8]. At the national level, lower agricultural GDP and export earnings are important factors. At the global level, negative impacts on carbon sequestration, climate change, desertification, loss of agricultural land productivity, damage to biodiversity conservation, and pollution of transnational water resources need to be accounted [2,9]. While a reliable estimate of the economic costs of land degradation in Uzbekistan is currently unavailable, the World Bank estimates an annual cost of US$1 billion at economic prices due to the deterioration of the country's production base. This deterioration is caused by the lack of maintenance of irrigation and drainage systems, significant water losses, severe soil salinization, and declining crop yields [10–12]. A comprehensive study would be required to fully evaluate the economic costs of land degradation [13,14]. Such comprehensive studies not only consider economic damages but also utilize information technologies in assessing land degradation. Remotely sensed information, in particular, has the potential to effectively monitor and assess dynamic land degradation processes. Accurately evaluating land degradation from remote sensing images is important as it saves human labour, time, and effort compared to collecting soil salinity data in the field [15,16]. The objective of this study is to assess desertification in Uzbekistan by analysing remotely sensed images over a long-term period and comparing these findings with formal soil productivity [17–19].

The use of geospatial data and GIS technologies enables the monitoring and mapping of desertification processes, providing valuable insights into landscape dynamics and environmental change in the Mirzachul area [20]. Addressing knowledge gaps, integrating data, and promoting collaboration among stakeholders are crucial for advancing desertification research and supporting sustainable land management practices in the region [21].

2 Material and methods

2.1 Study area

Uzbekistan is a country in Central Asia, situated between the Syrdarya and Amudarya rivers. It has a total territory of 448 thousand km^2, with 272 thousand km^2 being agricultural lands. The natural features of Uzbekistan include a combination of large valleys, foothills, and mountain regions. The northwest and west of the Republic are desert, while the south and southwest consist of foothills and mountains [18]. For the case study, we have chosen the Mirzachul area, which is located between latitude: 41° 45' 54" N and longitude: 67° 42' 07" E, and latitude: 40° 20' 17" N and longitude: 67° 14' 23" E (Figure 1). Mirzachul is a steppe-arable land covering an area of just over 1 million hectares.

Research area is situated on the left bank of the Syrdarya river, starting from the Farkhad water reservoir, where the river valley narrows, and is sandwiched between the spurs of the Turkestan ridge on one side and the mountain "Molgoltau" on the other. The climate in this

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area is typically continental, with mild winters and hot, dry summers. The average annual temperature is around +12.5°C, with July being the hottest month at an average daily temperature of +27…+30°C. January is the coldest month, with monthly air temperatures sometimes dropping to -70°C. The absolute maximum temperature varies [22].

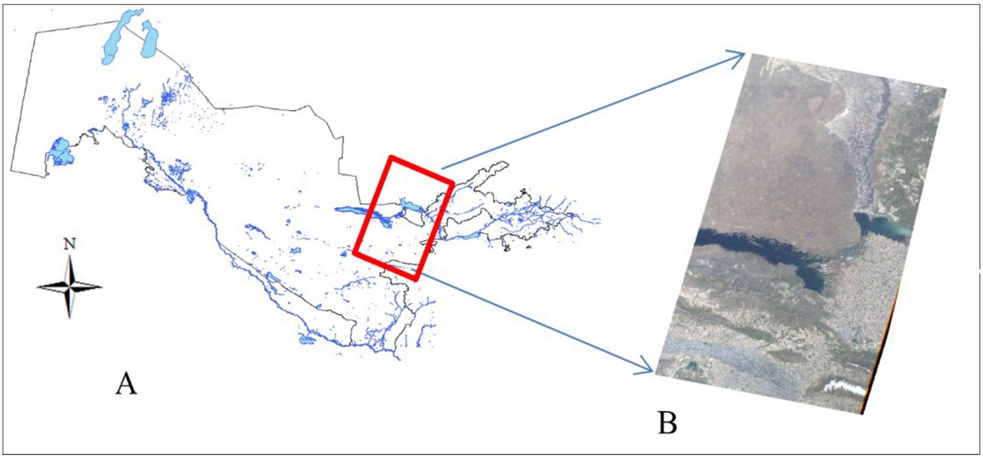

Fig. 1. Map of study area (A: Thematic map; B: Satellite image).

The temperature that occurs in the shadows is +480°C. The vegetation period for cotton, wine, and orchards lasts for 210-220 days, starting from +10°C in spring and ending at +10°C in autumn. The total temperature during the vegetation period exceeds 4500, and there are 150 clear days [6,23]. The Mirzachul depression is a large hydrogeological basin that formed due to the combined effect of ground and surface runoff from the Turkestan range, as well as the influence of the waterbodies of Syrdarya. Prior to the start of irrigation, the groundwater mostly lies at greater depths (10-20 meters or more). Elevated groundwater levels were only observed in the Jetisay and Sardoba depressions (3-5 meters) and on the slopes of the Shuruzak depression (5-10 meters) [24–26].

2.2 Data

In this study, we analysed satellite images from Landsat 5 TM and Landsat 8 OLI with a resolution of 30x30 meters. The specific path and row of the images were obtained from reliable sources such as earthexplorer.usgs.gov and glovis.usgs.gov. To ensure accuracy, the images were rectified to the Gauss-Krueger coordinate system that is appropriate for this study [27,28]. We carefully selected the dates of the satellite images based on the monitoring dates of arable land conducted by "Tuproq Bonitirovkasi" LLC, which is under the supervision of the "Uzgeodezkadastr" State Committee. The specific dates of the satellite images used in this study can be found in Table 1 below:

Table 1. The dates of Landsat images acquisitions.

Name of sensor	Dates of Landsat images	Year of land productivity monitoring
Landsat 5 TM	34446	1994
Landsat 5 TM	36270	2004
Landsat 8 OLI	38465	2014
Landsat 9 OLI	40286	2024

April has been selected as the date simply because this is where the vegetation cover occurs.

As the base for our scientific investigation, we created the soil content map (National Atlas of Uzbekistan, 2022) to identify the location of the study region, Mirzachul, where there is a sandy bare soil layer and a loamy soil layer on the surface (Figure 2).

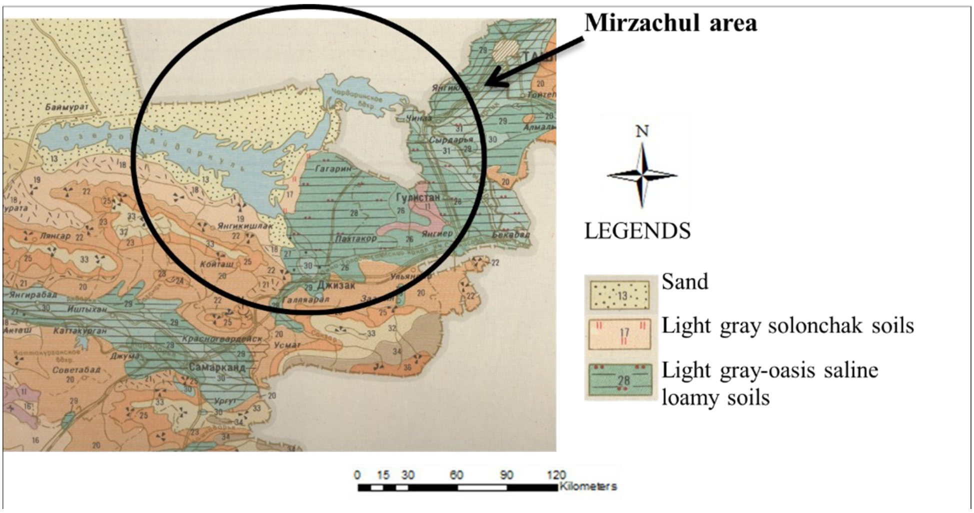

Fig. 2. Soil content map of Mirzachul area.

A soil map was created illustrating the sandy soil surrounding Aidarkul Lake, the loamy soil covering half of the Mirzachul area, and the solonchak (saline) soil that separates the sandy soil and the oasis. In the following steps, we will examine how sandy soil contributes to land degradation over a period of several years by analysing remotely sensed images [29,30].

2.3 Geospatial data and GIS technologies

To conduct this analysis, we will utilize various remote sensing techniques, such as vegetation indices, to map the potential extent of desertification in the Hunger Steppe. Specifically, we have chosen to use NDVI, SAVI, and WDVI as these indices operate in different ways - ratio-based, soil-adjusted, and orthogonal-based, respectively. The first index we will analyse is NDVI (Normalized Difference Vegetation Index), which was initially conceptualized by Kriegler et al. (1969) and further explained by Rouse et al. (1973) according to Bannari et al. (1995).

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \quad (1)$$

The NDVI (Normalized Difference Vegetation Index) is calculated by using the mean reflectance values for the red channel (Band 3) and the near infrared channel (Band 4) of Landsat TM/ETM+ images. This index is highly sensitive to the presence of green vegetation and can accurately predict agricultural crops and precipitation in semi-arid areas. It is widely used in regional and global applications for studying vegetation conditions. The NDVI has been proven to effectively describe vegetation variations, even in the presence of atmospheric effects [31].

The subsequent index to be discussed is the Soil Adjusted Vegetation Index (SAVI), which can be seen as a combination of ratio indices (such as NDVI) and orthogonal indices (like PVI). What sets this index apart is its innovative approach of creating a straightforward model that effectively characterizes the soil-vegetation system. The SAVI can be mathematically defined by the following equation [32].

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

Where L represents the soil adjustment factor, Huete (1988) demonstrated through the use of a simplified radiative transfer model that a value of L = 0.5 offers the most effective adjustment. This adjustment minimizes the secondary backscattering effect caused by canopy-transmitted soil background reflected radiation. The SAVI (Soil-Adjusted Vegetation Index) ranges from -1.5 to 1.5. When L is set to zero (L = 0), the SAVI is equivalent to the NDVI (Normalized Difference Vegetation Index). Therefore, we adopt the optimal value of L as 0.5.

If the ratio between the reflectance factors of bare soil in the red and near-infrared spectral bands remains unaffected by soil content, it is feasible to determine the corrected near-infrared reflectance by employing a weighted difference vegetation index (WDVI) based on the measured near-infrared and red reflectance values [33]. The WDVI scale ranges from 0 to 40, and its computation follows the formula:

$$WDVI = NIR - C \times RED \qquad (3)$$

According to Clevers (1989), the classification of object types differs from the other indices mentioned earlier. Vegetation cover begins at just over 20 when leaf area contributes to its coefficient of 1, along with other types of objects as shown in Table 2 [34]).

Table 2. Equivalents of classes on different vegetation indices (Dubinin, 2002; Xue et al. 2017; Huete, 1988; Mobasheri et al. 2010; Clevers, 1993; Clevers and Verhoef, 1993).

Types of classes	NDVI values	SAVI values	WDVI values
Dense vegetation	>0.70	>1.126	>35
Moderate vegetation (including agricultural crops)	0.40-0.69	0.91-1.125	30-34
Steppe	0.30-0.39	0.46-0.90	21-29
Bare soil	0.20-0.29	0.256-0.45	16-21
Desert	0.10-0.19	0.16-0.255	11-15
Cloud	0	0.06-0.15	2-10
Water	-1…0	-1.5…0	1

2.4 Methodology

Before the implementation of these remote sensing tools, there is a need for atmospheric correction of satellite images. This is because all of the mentioned indices are susceptible to atmospheric influence, which significantly compromises the output of the analyses (Hadjimitsis et al., 2010). In order to map and monitor land degradation, the Soil Map of Uzbekistan (Atlas, 1982) created by the Former Soviet Union was used as a secondary data source. This map assisted in determining the distribution of soil types in the case study area. The methodology flowchart (Fig.3) illustrates the steps taken in conducting the research [35].

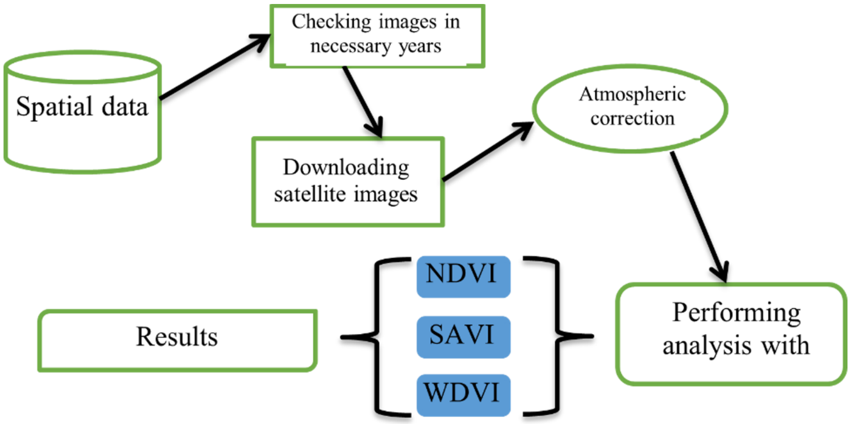

Fig. 3. Flowchart of methodology.

3 Results

3.1 Analysis of satellite images

The monitoring and mapping of desertification were carried out using three vegetation indices, as previously mentioned, from 1994 to 2024. The total area of the case study site, as determined by the remotely sensed images, is 6,515,467 hectares. The analysis of the first ratio-based vegetation index, NDVI (Figure 4), indicated that in 1994, sandy soil was dominant, with the exception of the southern and northeastern parts of the Mirzachul area. However, over the course of 30 years, there has been a significant decrease in this dominance, accompanied by a notable increase in steppe and moderate vegetation, including agricultural croplands.

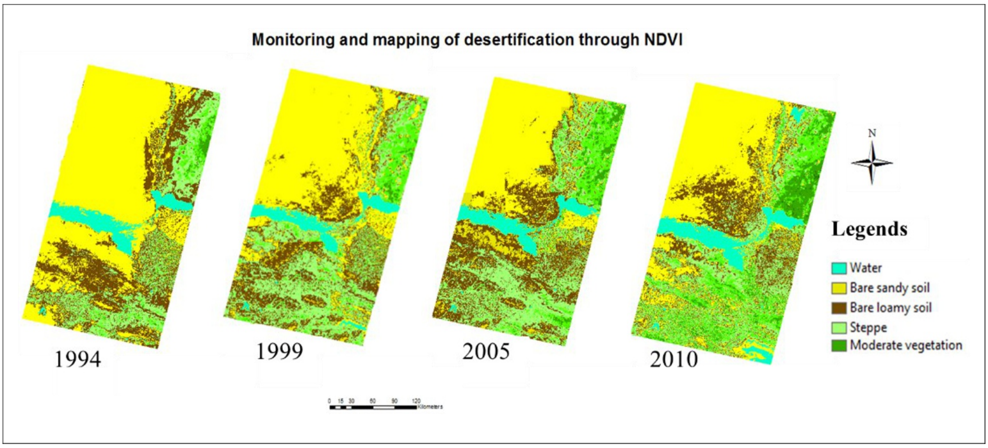

Fig. 4. Illustrations of land cover change by NDVI.

Interestingly, the area of Aidarkul Lake has also experienced a negligible expansion. However, in 2010, a notable change was observed, as a sandy soil area replaced the previously bare loamy soil. This change was evident in the classified image (Figure 4), where the Normalized Difference Vegetation Index (NDVI) showed similar results at the beginning of the year.

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Subsequently, the soil-adjusted vegetation index (SAVI) was employed in the analysis process, resulting in significantly different maps compared to the NDVI tool (Figure 5).

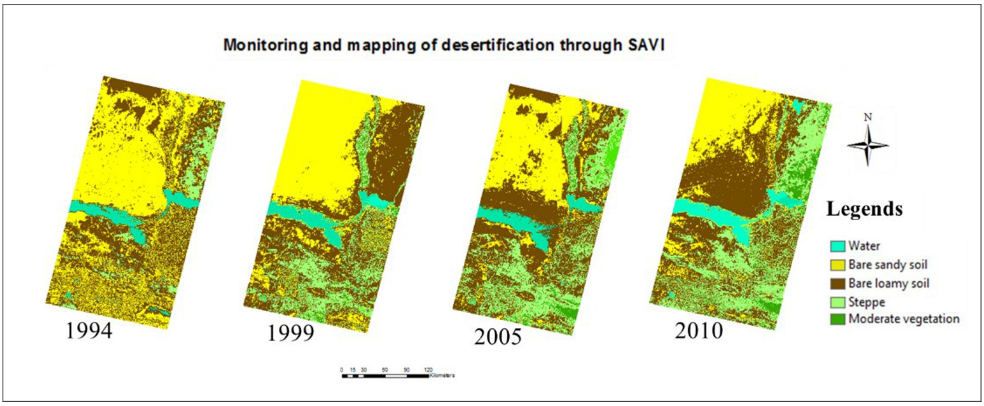

Fig. 5. Maps of land cover change by SAVI.

In these maps, sandy soil dominated in 1994 and showed a significant decrease towards the end of the period. However, when comparing NDVI mapping to SAVI mapping, it is clear that vegetation cover, such as grasslands or steppes in the southern part of Mirzachul, did not appear in the SAVI mapping. Canopy cover was absent in the northeastern part of the case study in 2005. Areas with loamy bare soil content were present in the upper part in both 1994 and 2005, but they disappeared in 2010, relocating to the centre of the study area. Although canopy cover moderately increased during the same periods in the SAVI analysis, NDVI demonstrated higher vegetation coverage in 2010.

The WDVI analysing was used (Figure 6, an orthogonal-based vegetation index, indicated the dominant class as bare loamy soil (sandy soil was identified in NDVI and SAVI analyses) in 1994. However, the extent of steppe territory was much smaller compared to the other results.

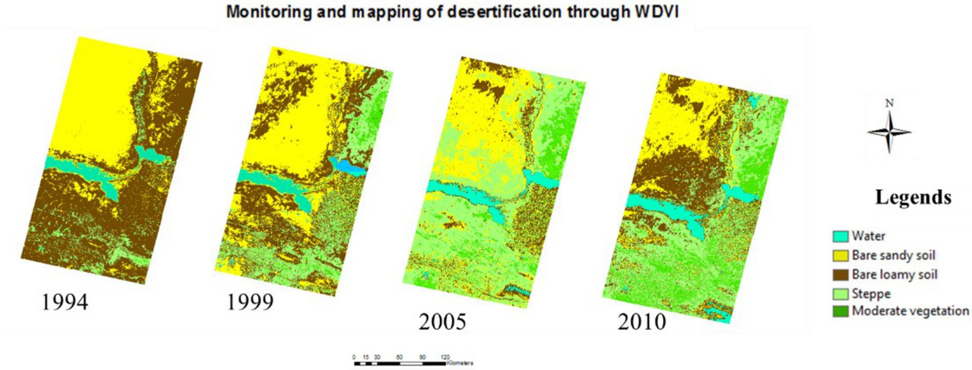

Fig. 6. Map of land cover change by WDVI.

On the one hand, the WDVI exhibits clear sensitivity to both soil and vegetation characteristics, as evidenced by its ability to accurately depict the steppe area and its pronounced differences compared to other indices in 2014. On the other hand, the orthogonal index in 2024 demonstrates a soil-adjusted vegetation index, particularly in terms of greenness. However, its effectiveness in accurately assessing water resources is best observed when utilized as a ratio-based vegetation index throughout the entire period.

3.2 Results of Analyses

Therefore, we constructed a table (Table 3) that presents the precise values for each category in the map: water, bare sandy and loamy soils, steppe or grasslands, and moderate canopy cover including agricultural crops.

Table 3. Area of each legend classified correctly in hectares.

VIs	Types of classes	1994	2004	2014	2024
NDVI	Water	344056	359741	370882	379263
	Bare sandy soil	4490518	3127424	2568746	2254647
	Bare loamy soil	498661	390927	456083	423505
	Steppe	863981	2280413	2410723	2315259
	Moderate vegetation (including agricultural crops)	318252	356961	709033	1142793
SAVI	Water	312489	339074	345159	371587
	Bare sandy soil	4756290	3257733	2475877	1628867
	Bare loamy soil	1042474	1172784	1325712	1743672
	Steppe	325773	1498557	1846950	1989485
	Moderate vegetation (including agricultural crops)	78441	247319	521769	781856
WDVI	Water	331587	348771	359521	372843
	Bare sandy soil	2663185	2441032	1856908	1503093
	Bare loamy soil	3127424	1789485	290928	1112165
	Steppe	301454	1563712	3055465	2154640
	Moderate vegetation (including agricultural crops)	91817	372467	952645	1372726

In the before mentioned table, the water resource status in the Mirzachul area exhibited a marginal improvement. However, the trend of bare loamy soil varied, as indicated by fluctuations, increases, and reductions in three distinct vegetation indices: NDVI, SAVI, and WDVI, respectively.

Our study revealed that the State Cadastre agency of the Republic of Uzbekistan monitored the points of land productivity (bonitet) on Mirzachul in 1994, 2004, 2014, and 2024. The recorded values were 41.1, 43.8, 47.6, and 51.2 out of 100 points, respectively (Uzgeodezkadastr, 2010). Both the government monitoring and our study demonstrate an improvement in land quality for agriculture. It is important to note that this scientific research was exclusively conducted within the territory of Uzbekistan.

4 Discussion

The study area underwent a major spatial change with the conversion of bare loamy soils or deserts into vegetated areas. This conversion trend was particularly noticeable in the southern and northwestern regions of Mirzachul in 2010. The rapid development of industries and agriculture, along with the expansion of agricultural lands following the reforms during the Republic's independence, contributed to this change. Both international and local laws and policies have facilitated the consistent growth rate of vegetated areas since 1991. This period of reforms was significant for Central Asian countries as it marked their transition from a planned economy to a market economy. The comprehensive social and economic development during this time provided the material foundation for urbanization and population growth, leading to a larger-scale expansion of vegetated areas. These findings align with the scientific research conducted by Blaikie and Brookfield (2015), which indicates a decrease in bare soils and attributes it to high population pressure, limited alternative livelihood opportunities, and rapid rural development.

At the same time, some authors [15,16,36] suggest that despite the poor natural conditions of these areas and significant desertification, especially towards the end of the 20th century, variations in the images captured during the same observation period could be attributed to global climate changes. The results also imply that different weather conditions and precipitation amounts can be reflected in different values of indices and the classification results themselves.

5 Conclusion

Remote sensing is an invaluable tool in the field of environmental sciences as it provides us with spatial data necessary for mapping and monitoring land degradation. The maps depicting desertification reveal the retreat of sandy soils, particularly indicating that arable steppe land is unlikely to be degraded. In our research, we employed three vegetation indices which yielded similar results in calculating sandy soil. However, there was a significant disparity in the calculation of canopy pixels. Our findings indicate that there was a substantial difference between sandy bare soil and steppe trends in the early stages of our study in 1994, covering approximately 4.5 million hectares and 250,000 hectares, respectively. However, by 2024, the sand content in the topsoil had decreased sharply by approximately 50%, covering an area of over 1.5 million hectares. In contrast, the steppe area showed an upward trend, expanding to 2 million hectares in 2024. Our scientific study reveals that desertification is currently not a concern in the Mirzachul area. Future studies may involve statistical analyses of the trends outlined in this article.

References

1. H. Yin, A. V. Prishchepov, T. Kuemmerle, B. Bleyhl, J. Buchner, and V. C. Radeloff, Remote Sensing of Environment **210**, 12 (2018)
2. R. S. Dwivedi, G. Z. Xian, H. R. Sensing, O. F. Vegetation, M. Chen, D. Fahrner, D. Arribas-bel, F. Rowe, R. Navalgund, Q. Weng, ส. ไทรทับทิม, L. Saganeiti, F. Amato, G. Nolè, M. Vona, B. Murgante, Y. Jamei, P. Rajagopalan, Q. C. Sun, D. N. Das, S. Chakraborti, G. Saha, A. Banerjee, D. Singh, ส. ไทรทับทิม, X. Xiao, S. Boles, S. Frolking, C. Li, J. Y. Babu, W. Salas, B. Moore, J. D. Kalma, T. R. McVicar, M. F. McCabe, JRC European Commission, A. Aghakouchak, A. Farahmand, F. S. Melton, J. Teixeira, M. C. Anderson, B. D. Wardlow, C. R. Hain, M. S. Rahman, H. Mohiuddin, A. A. Kafy, P. K. Sheel, L. Di, M. Zribi, N. Baghdadi, M. Nolin, M. El-hag, A. Allbed, L. Kumar, A. H. E. Nahry, R. R. Ali, A. A. E. Baroudy, B. R. Parida, H. A. A. Gaznayee, A. M. F. Al-Quraishi, P. Shanmugapriya, S. Rathika, T. Ramesh, P. Janaki, N. Teshaev, B. Mamadaliyev, A. Ibragimov, S. Khasanov, J. Vojteková, M. Vojtek, A. Bannari, D. Morin, F. Bonn, A. R. Huete, W. G. Alemu, G. M. Henebry, and G. Foody, Advances in Remote Sensing **8**, 468 (2020)
3. D. Rivera-Marin, J. Dash, and B. Ogutu, Journal of Arid Environments **206**, 104829 (2022)
4. P. Li, P. Chen, J. Shen, W. Deng, X. Kang, G. Wang, and S. Zhou, Sustainability **14**, 7470 (2022)

5. L. Cui, Scientific Programming **2021**, e7557175 (2021)
6. N. Csikós and G. Tóth, Agricultural Systems **204**, 103560 (2023)
7. S. Goibberdiev, G. Ikromkhodjaev, Z. Tajekeev, T. Ismailov, U. Mukhtorov, and I. Aslanov, E3S Web of Conf. **443**, 06013 (2023)
8. I. Aslanov, N. Teshaev, K. Khayitov, U. Mukhtorov, J. Khaitbaeva, and D. Murodova, E3S Web of Conf. **443**, 06015 (2023)
9. R. W. Doerge, Nature Reviews Genetics **3**, 43 (2002)
10. M.Khamidov, A.Inamov, U.Islamov, Z.Mamatkulov, B.Inamov. E3S Web of Conf., **386**, 02001 (2023).
11. M.Reimov, Z.Mamatkulov, U.Shermanov, R.Oymatov, A.Khamraliev and B. Abdurashitov. E3S Web Conf., **386**, 01002 (2023).
12. A.Khamraliev, Z.Mamatkulov, I.Musaev, B.Saipova, R.Oymatov and N.Mirjalolov. E3S Web Conf., **386**, 01010 (2023).
13. M.Avlakulov, B.Matyakubov, I.Kodirov. AIP Conf. Proc., **2612**, 050032 (2023).
14. R. K. Oymatov, Z. J. Mamatkulov, M. P. Reimov, R. I. Makhsudov, and R. N. Jaksibaev. IOP Conf. Ser.: E. and Envir. Sci. **868**, (2021)
15. Matyakubov, B., Nurov, D., Teshaev, U. Kobulov, K. IOP Conf. Ser.: E. and Envir. Sci., **1138(1)**, 012016 (2023).
16. M.Wojtaszek, L.Ronczyk, Z.Mamatkulov, M. Reimov E3S Web of Conf. **227**, 01001 (2021).
17. Khamidov, M., Inamov, A., Islomov, U., Mamatkulov, Z. E3S Web of Conferences, 365, 01008 (2023).
18. Mamatkulov, Z., Abdivaitov, Kh., Hennig, S., Safarov E. Int. J. Geoinformatics **18 (1)** (2022).
19. M. Akbari, M. J. Shalamzari, H. Memarian, and A. Gholami, Ecological Indicators **111**, 106011 (2020)
20. R. Kulmatov, A. Taylakov, and S. Khasanov, Sustain. Water Resour. Manag. **10**, 36 (2024)
21. G. Gutman, J. Chen, G. M. Henebry, and M. Kappas, editors , (Springer International Publishing, Cham, 2020)
22. A. Rabbimov, S. Karshiev, L. Gafurova, and G. Nabieva, BIO Web Conf. **82**, 02028 (2024)
23. M. Köberl, H. Müller, E. M. Ramadan, and G. Berg, PLoS ONE **6**, e24452 (2011)
24. A. Toure, I. Daou, and H. Bokar, (2023)
25. P. S. Thenkabail, M. Schull, and H. Turral, Remote Sensing of Environment **95**, 317 (2005)
26. J. Tan, D. Yu, Q. Li, X. Tan, and W. Zhou, Scientific Reports **10**, 1 (2020)
27. E. Sertel, B. Ekim, P. Ettehadi Osgouei, and M. E. Kabadayi, Remote Sensing **14**, 4558 (2022)
28. M. Mariye, L. Jianhua, and M. Maryo, All Earth **0**, (2022)
29. Y. Ma, D. Lyu, K. Sun, S. Li, B. Zhu, R. Zhao, M. Zheng, and K. Song, Land **11**, 1810 (2022)
30. A.-A. Kafy, A. Al Rakib, K. S. Akter, Z. A. Rahaman, A.-A. Faisal, S. Mallik, N. M.

R. Nasher, Md. I. Hossain, and Md. Y. Ali, Environmental Challenges **4**, 100187 (2021)

31. A. Bannari, D. Morin, F. Bonn, and A. R. Huete, Remote Sensing Reviews **13**, 95 (1995)
32. A. R. Huete, Remote Sensing of Environment **25**, 295 (1988)
33. J. G. P. W. Clevers and W. Verhoef, Remote Sensing Reviews **7**, 43 (1993)
34. M. E. D. Chaves, M. C. A. Picoli, and I. D. Sanches, Remote Sensing **12**, 3062 (2020)
35. P. Duarte, Janus.Net **5**, 48 (2014)
36. A. J. Dougill, D. S. G. Thomas, and A. L. Heathwaite, Annals of the Association of American Geographers **89**, 420 (1999)