

Improving land cover classification in drylands with MSAVI: Evidence from the South Aral Seabed Post-print

Authors: Shahzoda ALIKHANOVA, Cristina TARANTINO, Joseph William BULL, Shahzoda ALIKHANOVA

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Abstract

The South Aral Seabed is an extreme dryland ecosystem undergoing rapid transformation yet remains misrepresented or absent in global land cover datasets. Conventional vegetation indices, specifically the Normalized Difference Vegetation Index (NDVI), perform poorly in such environments due to their limited ability to distinguish sparse vegetation from highly reflective saline and sandy soils. This study evaluated the effectiveness of the Modified Soil Adjusted Vegetation Index (MSAVI) for improving land cover classification in the South Aral Seabed and conducted a decadal analysis of land cover change between 2013 and 2023 using Landsat 8 imagery (30 m resolution). A spectral index-based classification framework was developed, combining MSAVI with the Normalized Difference Water Index (NDWI) and Salinity Index 1 (SI1) to reduce spectral confusion between vegetation, saline soils, and surface water. The MSAVI-based classification achieved an overall accuracy of 77.96% (Kappa coefficient=0.71), supported by 313 field-collected validation points from 2023. While the multi-index approach enabled finer discrimination of ecologically important classes, particularly separating salt pans from solonchak soils, it resulted in a lower overall accuracy (73.80%), highlighting a trade-off between class separability and classification performance. Land cover change analysis revealed a highly dynamic landscape, with 52.96% of the study area transitioning between classes over the decade. Transformed areas (16,893 km²) exceeded stable zones (15,004 km²), driven primarily by rapid desiccation and salinization. Solonchak soils increased at an annual rate of 5.58%, while surface water bodies declined by 4.83% per year. Concurrently, sparse or distressed vegetation increased by 1.43% annually, reflecting ongoing afforestation efforts. This study provides the first MSAVI-based and medium-resolution land cover baseline for the South Aral Seabed and demonstrates that soil-adjusted vegetation indices are essential for reliable dryland classification where conventional indices fail. The proposed

spectral index framework offers a replicable methodology applicable to other global drylands facing similar land degradation and restoration challenges.

Full Text

Preamble

J Arid Land (2026) 18(2): 185-201 doi: 10.1016/j.jaridl.2026.02.001; CSTR: 32276.14.JAL.20250369 Improving land cover classification in drylands with MSAVI: Evidence from the South Aral Seabed Shahzoda ALIKHANOVA1*, Cristina TARANTINO2, Joseph William BULL1

2 National Research Council of Italy, Institute of Atmospheric Pollution Research, Bari 70126, Italy

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Keywords: land cover classification; Aral Sea; drylands; Modified Soil Adjusted Vegetation Index (MSAVI); spectral indices; Aralkum Desert; remote sensing Citation: Shahzoda ALIKHANOVA, Cristina TARANTINO, Joseph William BULL. 2026. Improving land cover classification in drylands with MSAVI: Evidence from the South Aral Seabed. *Journal of Arid Land*, 18(2): 185–201. <https://doi.org/10.1016/j.jaridl.2026.02.001>; <https://cstr.cn/32276.14.JAL.20250369>

1 Introduction

Land cover mapping is essential for understanding, monitoring, and detecting historical trends in *Corresponding author: Shahzoda ALIKHANOVA (E-mail: shahzoda.alikhanova@biology.ox.ac.uk) Received 2025-10-22; revised 2025-11-23; accepted 2025-12-30 © 2026 Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, and Science Press. Publishing services by Elsevier B.V. on behalf of KeAi Communications Co. Ltd.

This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>). <http://jal.xjegi.com>; <https://www.keaipublishing.com/en/journals/journal-of-arid-land/> JOURNAL OF ARID LAND 2026 Vol. 18 No. 2 land cover change across temporal and spatial scales, and it serves as a vital tool for evidence-based natural resource management and policy decisions (Ali et al., 2022; Venter et al., 2022). As an Essential Climate Variable (ECV) identified by the Global Climate Observing System (GCOS), land cover plays a critical role in assessing impacts on natural resources and ecosystem services, including carbon pool changes relevant to climate mitigation and adaptation (Bojinski et al., 2014; WMO, 2022). Accurate land cover data support comprehensive climate system understanding, underpin climate risk evaluation, guide climate mitigation strategies, and contribute to attributing climatic events to their causes (WMO et al., 2022). Land cover change is also widely recognized as a direct driver of biodiversity loss and impacting ecosystem services, both globally and within Central Asia (Martín-López et al., 2018; Venter et al., 2022). Because of these broad implications, land cover reporting is embedded in international frameworks such as the United Nations Framework Convention on Climate Change (UNFCCC), United Nations Convention to Combat Desertification (UNCCD), and Sustainable Development Goals (SDGs), making reliable land cover assessments vital for tracking progress toward global environmental targets (Andries et al., 2022; Safaei et al., 2022).

Global land cover maps and remote-sensing products have improved substantially over recent decades (Friedl et al., 2002; Smith et al., 2019). Still, their reliability often declines when applied at regional or local scales, partly due to the lack of a unified global classification system and the difficulty of capturing fine-scale landscape variation (Gilić et al., 2023). Moreover, considerable uncertainties persist when applying these global land cover products to location-specific studies, complicating their utility for regional climate modelling. Land cover is inherently dynamic, with few areas remaining unaffected by human

activity (Friedl et al., 2002). These limitations are especially problematic for dryland ecosystems, which are ecologically complex and span multiple climatic zones (Smith et al., 2019; Wang et al., 2023).

Although various land cover classification methods exist, their accuracy depends on local landscape characteristics, class definitions, and high-quality ground truth data (Khatami et al., 2016). While remote sensing remains the most cost- and time-effective method for generating land cover maps and enabling long-term monitoring of landscape dynamics (Khatami et al., 2016; Andries et al., 2022), but its performance declines in heterogeneous dryland environments due to resolution limits, atmospheric effects, and the spectral similarity of bare soil and sparse vegetation (Khorram et al., 2012; Venter et al., 2022). Accurate land cover classification in drylands presents notable challenges due to sparse vegetation and exposed soils, which often exhibit similar spectral signatures (Bestelmeyer et al., 2015; Smith et al., 2019). Even widely used indices such as Normalized Difference Vegetation Index (NDVI) struggle in these settings because they cannot reliably disentangle soil and vegetation signals (Smith et al., 2019; Wang et al., 2023). As a result, coarse-resolution global datasets often fail to capture fine-scale variation in drylands, leading to substantial classification inaccuracies (Gilić et al., 2023). The Modified Soil Adjusted Vegetation Index (MSAVI) was developed as an advancement over traditional vegetation indices to improve vegetation detection in areas with bare soil background. MSAVI minimizes brightness influences from exposed soil through a self-adjusting soil adjustment factor, making it particularly effective in sparsely vegetated drylands where soil dominates the spectral signal (Qi et al., 1994). Unlike NDVI, which assumes a fixed soil line and underperforms in low-density vegetation due to soil noise saturation, MSAVI dynamically adapts to local soil variability, enhancing accuracy for subtle vegetation signals. This adaptability supports diverse dryland applications, including rangeland degradation monitoring (Belhadj et al., 2023), desertification assessment in sparse vegetation basins (Xu et al., 2023), and biomass mapping across global grasslands including desert steppes (Cai et al., 2024).

Challenges in accurately mapping land cover change are particularly pronounced in the former Aral Seabed due to rapid environmental transformation and heterogeneous surface conditions.

Despite afforestation efforts since the late 1980s (Forestry Agency of the Ministry of Ecology Environmental Protection and Climate Change of the Republic of Uzbekistan, 2023), the former Aral Seabed remains largely absent from major global mapping databases. When it does appear, it Shahzoda ALIKHANOVA et al.: Improving land cover classification in drylands... is often misrepresented, persisting as open water in outdated datasets or depicted as uniformly barren, thereby obscuring areas of vegetation establishment. For example, the 100-m Copernicus Global Land Cover map misclassifies portions of the South Aral Seabed as cropland or wetlands and incorrectly labelling vegetated patches as forests (Buchhorn et al., 2020). Besides, there is no documented application

of MSAVI in the South Aral Seabed, despite its suitability for conditions characterized by sparse vegetation, high salinity, and bright soil surfaces, which the dried-out seabed currently represents. These inconsistencies underscore the need for refined locally grounded approaches to accurately capture land cover dynamics in this rapidly evolving dryland ecosystem.

This study addressed the above-mentioned challenges through two research objectives: (1) evaluating the effectiveness of MSAVI and related spectral indices for detecting sparse vegetation in the South Aral Sea, where soil brightness often obscures vegetation signals; and (2) mapping land cover change across the South Aral Seabed and identifying temporal trends. These objectives aim to provide a more reliable and locally grounded understanding of land cover dynamics in this ecologically vulnerable region.

2.1 Study area

For this study, the southern part of the former Aral Seabed (44.5°–45.5°N, 58.0°–60.5°E) located within the Republic of Uzbekistan was selected to map current land cover and to examine change dynamics over the past decade (Fig. 1 [Figure 1: see original paper]). Once the fourth-largest lake in the world, the Aral Sea has undergone severe desiccation since the 1960s, resulting in dramatic landscape transformations (Alikhanova and Bull, 2023). The exposed seabed, now known as the Aralkum Desert, spans approximately 68,104 km² (Nishonov et al., 2023; Banks et al., 2024).

Fig. 1 Spatial extent of the South Aral Seabed and distribution of 313 ground-truth sampling points collected in 2023 for classification calibration and accuracy assessment.

The study area exhibits an extreme continental climate characterized by hyper-arid conditions typical of Central Asian drylands. Annual precipitation is minimal, ranging 100–140 mm/a, often dropping below 100 mm on the exposed bottom of the former Aral Sea, with most precipitation occurring in winter and early spring. Summer temperatures frequently exceed 40°C, while winter temperatures can drop below -20°C, creating extreme thermal stress for vegetation (Löw et al., 2022; Wang et al., 2022; Nishonov et al., 2023).

The dominant land cover consists of exposed bare ground interspersed with sparse and patchy JOURNAL OF ARID LAND 2026 Vol. 18 No. 2 vegetation on sandy and saline soils. Vegetation cover and species composition are influenced by ongoing primary succession of the dried seabed, with satellite assessments indicating spatial variability in vegetation recovery—notably in the eastern part of the Aralkum Desert. Natural vegetation is limited to xerophytic shrubs adapted to extreme aridity and soil salinity, primarily saxaul species (*Haloxylon aphyllum* (Minkw.) Iljin and *Haloxylon persicum* (Bunge ex Boiss. & Buhse)), which form the basis of government-led afforestation projects aimed at stabilizing the degraded landscape. This combination of sparse and patchy vegetation distribution and extensive bare soil with high soil reflectance creates

substantial spectral confusion challenges for conventional vegetation indices, necessitating the use of soil-adjusted indices like MSAVI for accurate land cover classification (Alikhanova and Bull, 2023; Alikhanova et al., 2025).

2.2 Acquisition of remote-sensing data

Satellite images for the years 2013 and 2023 were acquired from the United States Geological Survey (USGS) Earth Explorer (<https://earthexplorer.usgs.gov/>), using Landsat 8 Collection 2, Level 2 products, which are atmospherically and radiometrically corrected to surface reflectance.

The chosen study period (2013–2023) corresponds to the launch of Landsat 8 and captures substantial post-2010 environmental changes, providing consistent and long-term coverage up to the 2023 field campaign. To fully cover the study area, six individual image tiles were required, as detailed in Table S1. To ensure image quality, we applied a cloud cover threshold of no more than 10.00% when selecting scenes.

The temporal window for image acquisition focused on June and July, chosen for their typically dry and cloud-free conditions in the region, allowing for clearer imagery and more reliable analysis.

Moreover, this period corresponds to the peak vegetative growth phase of saxaul (Haloxylon) and other desert shrub species used in afforestation efforts on the dried-out South Aral Seabed, providing stronger spectral signals, whereas the signals decline in later months, reducing reflectance accuracy (Bedareva, 2009).

2.3 Field data sampling and ground truthing

Field reference data were collected using a selective and non-random sampling strategy, resulting in 313 calibration points from homogeneous landscape patches. This approach ensured a balanced representation across all pre-identified land cover classes. We used the collected field reference data primarily to define and calibrate MSAVI threshold values based on observed vegetation characteristics. Additionally, 24 field plots were established to estimate percent vegetation cover for vegetation classes that could not be reliably separated using remote sensing alone (Alikhanova et al., 2025). Field campaigns were conducted across the South Aral Seabed on 12–20 April and 1–5 June 2023, and the spatial distribution of sampling locations is shown in Figure 1.

Due to the absence of historical field data and high-resolution imagery for earlier years, accuracy assessment was conducted exclusively for the 2023 land cover classification. The same set of 313 sampling points used for MSAVI threshold calibration was also employed for accuracy evaluation.

Although independent validation data are preferable, this overlap was necessitated by field constraints, particularly the lack of established roads in the study

area, which made many locations inaccessible. Most of the terrain had to be navigated off-road, with only a few viable driving routes, limiting the ability to collect separate ground-truth data across all land cover classes. Hence, a confusion matrix was generated using the available calibration points, and classification performance was assessed using overall accuracy, user's and producer's accuracy, and the Kappa coefficient.

3.1.1 Land cover classification

Based on field surveys that identified the most prevalent land cover types on the exposed bottom of the South Aral Sea, we classified the landscape into six categories: surface water, salt pan and Shahzoda ALIKHANOVA et al.: Improving land cover classification in drylands...solonchak, other barren land, sparse or distressed vegetation, dense and healthy vegetation, and wetland.

We combined salt pan and solonchak, as both are highly saline or salt-affected soils according to the Food and Agriculture Organization of the United Nations (FAO) soil classification system, into a single category (IUSS Working Group, 2015). This grouping simplified the classification process, recognizing that MSAVI is not specifically designed to differentiate varying levels of soil salinity. The other barren land class encompasses sandy soils distinct from pure sand or solonchak areas. These soils are considered suitable for afforestation efforts involving drought-tolerant desert plants (Breckle and Wucherer, 2012; Batsaikhan et al., 2020; Ma et al., 2021).

The sparse vegetation class includes saxaul shrubs and annual herbaceous vegetation.

Following the FAO vegetation taxonomy (Gregorio and Jansen, 2000), this class corresponds to areas with 10.00%–30.00% vegetation cover, producing a mixed soil-vegetation spectral response in MSAVI values. Notably, field observations revealed that some plots, though visually dense, exhibit low reflectance comparable to sparse vegetation due to notable degradation or dieback.

This spectral response, indicative of reduced chlorophyll content, prompted renaming the class to “sparse or distressed vegetation” .

The dense and healthy vegetation class comprises predominantly saxaul or mixed vegetation types covering more than 30.00% of the land surface, consistent with FAO definitions. Reeds are also included in this class, reflecting their distinct summer phenology and high spectral reflectance. Photographic representation of all land cover classes on the South Aral Seabed is provided in Figure 2 [Figure 2: see original paper].

3.1.2 Calculation of spectral indices

Spectral indices were computed from Landsat 8 Operational Land Imager (OLI) Level 2 surface reflectance products to distinguish vegetation greenness and

support the separation of vegetated classes from barren soil, salt-affected surfaces, and surface water. These indices enabled the masking of non-vegetated areas, such as salt pans and water bodies, prior to land cover classification, with MSAVI serving as the primary vegetation proxy. All calculations followed established formulations adapted to Landsat 8 band specifications. MSAVI was calculated from Landsat 8 OLI surface reflectance using the following formula (Qi et al., 1994; Barsi et al., 2014):

MSAVI

2 NIR+1

NIR Red where Near-Infrared (NIR) and Red reflectances correspond to Landsat 8 OLI Band 5 (0.85-0.88 μm) and Band 4 (0.64-0.67 μm), respectively.

Three soil salinity indices, namely the Normalized Difference Salinity Index (NDSI) (Abuelgasim and Ammad, 2019), Salinity Index 1 (SI1) (L w et al., 2022), and Salinity Index 4 (SI4) (Duan et al., 2022), were tested to discriminate salt pan surfaces from other non-vegetated land covers. These indices were selected for their high correlation rates in similar geographic conditions or the same particular area (Gorji et al., 2017; L w et al., 2022). The formulas for these indices are as follows:

NIR Red where Blue is the surface reflectance corresponding to Band 2 (0.45-0.51 μm) of Landsat 8 OLI sensor.

Among these, SI1 demonstrated the highest accuracy in reflecting field conditions and effectively discriminating salt-affected areas, as confirmed by ground-truth data. Areas with the highest salinity (salt pan) were subsequently extracted and masked from the MSAVI layer. In some areas, SI1 results coincided with areas identified by Normalized Difference Water Index JOURNAL OF ARID LAND 2026 Vol. 18 No. 2 Fig. 2 Field photographs illustrating the six land cover classes identified in the South Aral Seabed. All photographs were taken by Dr. Shahzoda ALIKHANOVA during field campaigns in April and June 2023. (a), a salt pan formed in the place of the dried-out lake; (b), salt crust; (c), typical solonchak soil with visible salt deposits on the surface; (d), solonchak soil; (e), barren land with clay soil; (f), barren land with sandy soil; (g), sparse vegetation; (h), distressed vegetation; (i), dense vegetation observed in April; (j), dense vegetation observed in June; (k), wetland containing herbaceous vegetation; (l), the water surface of the remaining part of the South Aral Sea.

Shahzoda ALIKHANOVA et al.: Improving land cover classification in drylands ... (NDWI) as surface water, highlighting the importance of applying indices sequentially to achieve maximum accuracy (i.e., masking with SI1 first, followed by NDWI). To allow a class-by-class comparison of the multi-index land cover classification with the MSAVI-based results, we merged the salt pan and solonchak classes into one class before computing the confusion matrix to match the

categories used in the MSAVI-based classification (Table S2).

In addition, surface water bodies were delineated using NDWI and Modified Normalized Difference Water Index (MNDWI) (Barsi et al., 2014; Miura et al., 2025), defined as:

MNDWI Green NIR Green NIR Green where Green corresponds to Landsat 8 OLI Band 3 (0.53–0.59 μm); and SNIR corresponds to the short-wave infrared Band 6 (1.57–1.65 μm) or Band 7 (2.11–2.29 μm) surface reflectance product (Barsi et al., 2014; Miura et al., 2025). Both SNIR bands were tested in this study, but Band 6 proved more effective in detecting surface water bodies and was therefore used in the subsequent analysis.

Further, validation using field observations, Google Earth Pro historical imagery, and Landsat 8 scenes indicated that NDWI provided more accurate water detection compared to MNDWI. The latter tended to misclassify certain salt marshes as open water, leading to overestimation.

Consequently, NDWI was retained as a more suitable index, and water bodies were masked from the MSAVI layer.

3.1.3 Accuracy assessment

To assess classification accuracy, first, we generated validation points using a stratified random sampling method to ensure balanced representation across all six land cover classes. These points were, then, used to compute a confusion matrix and derive standard accuracy metrics (Sokolova and Lapalme, 2009; Weih and Riggan, 2010; Chetjan et al., 2017; Congalton and Green, 2019).

To evaluate the model's performance on class-imbalanced data such as our field dataset, a weighted F1-score was also calculated (Kundu, 2022). The formula for the weighted F1-score is as follows:

Weighted F1-score $F1\text{-score}$, where W_i is the ratio of the number of samples of class i to the total number of samples; n is the number of classes; and F1-score is the harmonic mean of precision and recall, and can be estimated as follows (Sokolova and Lapalme, 2009): $\text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$ where Precision (user's accuracy) is the ratio of correctly identified positive instances to the total number of instances that the system labelled as positive; and Recall (producer's accuracy) is the ratio of correctly identified positive instances to the total number of actual positive instances in the ground truth data. The F1-score, in turn, is a metric that combines both Precision and Recall providing a single measure of a model's performance and balancing the trade-off between these two metrics (Sokolova and Lapalme, 2009).

3.2 Land cover change dynamics

Changes between the two maps produced for the baseline year (2013) and the end year (2023) were calculated in ArcGIS Pro (Environmental System Research

Institute (ESRI), Redlands, USA) to identify areas that transitioned from one class to another during this period. Following the UNCCD' s Good Practice Guidance on SDG 15.3.1 (proportion of land that is degraded over total land area) (Sims et al., 2020, 2021), land cover transition trends were identified.

Additionally, the annual rate of vegetation change was calculated using the formula (Zhang et al., 2021):

JOURNAL OF ARID LAND 2026 Vol. 18 No. 2 where KT is the annual rate of change in vegetation (%); U_a is the area of vegetation at the start year 2013 (km^2); U_b is the area of vegetation at the end year 2023 (km^2); and T is the duration of the study period in years (a). 100%,

4.1.1 Land cover classification using a single spectral index

The MSAVI-based classification for 2023 showed strong performance in distinguishing most land cover types, particularly surface water, salt pan and solonchak, and other barren land. The sparse or distressed vegetation class was more difficult to map and was often confused with either salt pan and solonchak or dense and healthy vegetation, likely because of overlapping spectral reflectance patterns (Table S2). The overall accuracy of the MSAVI-based map was 77.96%, with a Kappa coefficient of 0.71. The weighted F1-score of 0.78 was consistent with overall accuracy.

The final land cover maps for both years are shown in Figure 3 [Figure 3: see original paper].

Fig. 3 Modified Soil Adjusted Vegetation Index (MSAVI)-based land cover classification in the South Aral Seabed in 2013 (a) and 2023 (b)

4.1.2 A multi-index land cover classification using MSAVI, NDWI, and SI1

The combination of indices such as MSAVI, NDWI, and SI1 allowed for more precise identification of salt pans and enabled differentiation between salt pan and solonchak as separate classes (Fig. 4 [Figure 4: see original paper]).

The multi-index classification achieved an overall accuracy of 73.80% and a Kappa coefficient of 0.65 (Table S3). The weighted F1-score of 0.74 closely matched the overall accuracy, indicating consistent model performance and a robust level of classification quality across both majority and minority classes. Despite integrating multiple indices, the overall accuracy decreased by approximately 4.00% compared to the MSAVI-based approach. This reduction was primarily attributed to increased misclassification of other barren land as salt pan and solonchak.

This comparison demonstrated that while additional spectral indices enable finer class discrimination (e.g., separating salt pan from solonchak), the MSAVI-based

approach provides superior overall accuracy for broader land cover categories in this dryland environment.

Shahzoda ALIKHANOVA et al.: Improving land cover classification in drylands...Fig. 4 Land cover classification derived from multi-index combination of MSAVI, Normalized Difference Water Index (NDWI), and Salinity Index 1 (SI1) in the South Aral Seabed in 2013 (a) and 2023 (b)

4.2 Land cover change dynamics

Between 2013 and 2023, substantial transitions occurred among land cover classes within the South Aral Seabed. Over this decade, a total transition area of 16,893 km² was recorded, while areas that remained unchanged covered 15,004 km². An additional almost 28 km² could not be classified due to persistent cloud cover. Specifically, the most extensive transitions included: (1) from dense and healthy vegetation to sparse or distressed vegetation; (2) from other barren land to sparse or distressed vegetation; (3) from other barren land to solonchak; (4) from surface water to solonchak; and (5) from sparse or distressed vegetation to solonchak.

The most substantial “negative” changes observed were the reductions in the surface water class, indicating the ongoing desiccation of surface water bodies, while the most substantial “positive” changes were the decreases in salt pans. In this case, the reduction in the area of salt pans represented a positive scenario, as it indicated a decrease in salt-affected areas that are least suitable for afforestation, and which are subject to severe land degradation (Figs. 5 and 6).

The annual change rates for each land cover class revealed that wetland and surface water experienced the highest rates of decline. Conversely, the solonchak class, which represents highly saline soil, exhibited the highest annual increase rate, as detailed in Table 1 .

5.1 Evaluating spectral index-based land cover classification

The spectral index-based classification of the South Aral Seabed, primarily driven by MSAVI, achieved an overall accuracy of 77.96% and a weighted F1-score of 0.78. The F1-score, consistent with the overall accuracy, provides a robust assessment of map quality by accounting for both omission and commission errors (Foody, 2020; Verma et al., 2020). This level of performance for the MSAVI-based classification is notable given the extreme spectral complexity and harsh environmental conditions of this dynamic dryland system. It is comparable to, and in some cases exceeds, accuracies reported in recent dryland and Aral Sea Basin studies using advanced machine-learning methods, stratified classification approaches, or higher-resolution imagery (Liu et al., 2021; Polat and Kaya, 2021; Venter et al., 2022; Xu et al., 2024) . The classification results observed here are consistent with the demonstrated effectiveness of MSAVI in this region and in other Central Asian drylands, including its strong positive

correlations with above-ground biomass in the South Aral Seabed (Alikhanova et al., 2025), and across Central JOURNAL OF ARID LAND 2026 Vol. 18 No. 2 Fig. 5 [Figure 5: see original paper] Land cover transitions in the South Aral Seabed from 2013 to 2023 Fig. 6 [Figure 6: see original paper] Spatial distribution of land cover change and persistence in the South Aral Seabed from 2013 to 2023 Asian drylands more broadly (Batsaikhan et al., 2020; Zhang et al., 2023). Findings of this study demonstrate why MSAVI is particularly well-suited for capturing sparse vegetation in such challenging environments.

However, despite MSAVI's design to mitigate the influence of high soil brightness—a key limitation of its predecessor NDVI—soil background interference remains the principal source of classification error. Field validation showed that even marginal changes in index thresholds (0.01) influenced class boundaries, highlighting the fragility of vegetation index-based classification in landscapes dominated by bright and reflective soils (Smith et al., 2019). Persistent spectral
Shahzoda ALIKHANOVA et al.: Improving land cover classification in drylands
...Table 1 Area and annual change rate of each land cover class based on the Modified Soil Adjusted Vegetation Index (MSAVI) classification in the South Aral Seabed Land cover class Surface water Solonchak Salt pan Other barren land Sparse or distressed vegetation 10,575 Dense and healthy vegetation Wetland No data (clouds) Area (km²) 12,240 Annual change rate (%) confusion was observed among barren land classes (solonchak soils, other barren land, and salt pans) and in sparse or distressed vegetation, particularly where vegetation cover is extremely low.

This limitation is well-documented across arid and semi-arid areas: even soil-adjusted indices struggle when fractional vegetation cover approaches the bare-soil line, often below the 4.00% threshold used to define bare land (Gregorio and Jansen, 2000; Smith et al., 2019; Zandler et al., 2022; Xu et al., 2024). Initial attempts to discriminate eight classes by vegetation greenness rather than density (surface water, salt pan, solonchak soil, sandy soil, low vegetation greenness, moderate vegetation greenness, high vegetation greenness, and wetland) confirmed this persistent confusion, particularly for low-density vegetation classes.

Additional classification challenges arise from species- and environment-specific factors.

Distinguishing saxaul species is difficult because young black saxaul (*Haloxylon ammodendron* (C.A.Mey.) Bunge ex Fenzl and *H. aphyllum*) occasionally exhibits higher near-infrared (NIR) reflectance than white saxaul (*H. persicum*), leading to misclassification of low-density stands as high-density. Dense afforested areas sometimes display low MSAVI values, likely reflecting vegetation stress, plant age, or groundwater depletion beneath mature stands. Environmental moisture further complicates classification, with bare soils near water bodies occasionally misclassified as vegetation, consistent with previous observations of *Haloxylon*-dominated shrublands where MSAVI and NDVI respond to both biomass and non-photosynthetic factors such as soil moisture (Batsaikhan et al., 2020; Liu et al., 2023; Yang, 2025).

To overcome the limitations of single-index classification, a hybrid approach was developed by combining MSAVI with a salinity index (SI1) and a water index (NDWI). This approach extends prior Aral Sea studies (Kim et al., 2020; Berdimbetov et al., 2021a, b; Duan et al., 2022; Bao et al., 2024) that relied primarily on NDVI. While the hybrid classification improves separation of major classes and ecologically important features, it introduces new challenges: SI1 sometimes fails to distinguish moist solonchak from sandy soil, and some salinity indices (e.g., SI4) misclassify pure salt crusts as white sand. These issues, coupled with the need for precise thresholding, underscore the persistent limitations of spectral indices in highly mixed and spectrally analogous drylands.

Although the MSAVI-based classification achieved slightly higher overall accuracy (4.16%) than the multi-index approach, the latter was selected for analyzing land cover transitions because it allowed monitoring of finer transitions among ecologically important classes, such as changes involving salt pans and their conversion to or from other classes. This improved approach provides a more nuanced understanding of landscape dynamics, which is essential for assessing ecological change and guiding restoration strategies.

Moving forward, achieving the accuracy needed for detailed dryland ecosystem monitoring will likely require transitioning from single- or multi-index thresholding to advanced classification algorithms (e.g., Random Forest and Support Vector Machines) that leverage the JOURNAL OF ARID LAND 2026 Vol. 18 No. 2 full multi-spectral band stack, topographic variables, and spatial texture features to better capture the complexity of the landscape (Yang, 2025). Nevertheless, rigorous and locally informed interpretation and field verification remain indispensable for reliable dryland land cover mapping, regardless of the classification methodology, which our study provides.

5.2 Land cover change dynamics

Analysis of land cover transitions in the South Aral Seabed from 2013 to 2023 revealed a highly dynamic landscape, with transformed areas (16,893 km²) exceeding stable zones (15,004 km²), meaning that at least 52.96% of the study area changed land cover over the decade. This magnitude of change aligns with basin-wide studies reporting approximately 50.00% of surface water area converted to bare land from 1992 to 2015 (Su et al., 2021), and broader assessments indicating that 36.50% of the Aral Sea Basin experienced land degradation from 1982 to 2015, primarily in lower-basin areas near the Aral Sea (Berdimbetov et al., 2021b).

The observed transitions reflected two major processes: environmental degradation and afforestation. The most pronounced negative trend was the decline in surface water bodies at an annual rate of 4.83%, and the corresponding expansion of solonchak soils at the annual rate of 5.58%. This transition suggested a direct conversion of receding water surfaces to highly saline and clay-rich solonchak and salt pans. Current monitoring indicates that the Aral Sea now covers

only 8.00% of its 1960 surface area, consistent with long-term desiccation trends without reliable surface water recharge (Rawat et al., 2025; Yang, 2025). Predictive land cover models that project the continued rapid expansion of salinized soils and barren lands through 2025 and beyond, strongly corroborate these observed trends (Shen et al., 2019).

Conversely, the annual increase of 1.43% in sparse vegetation reflected the positive impact of intensive afforestation efforts that have dramatically accelerated across the Aralkum Desert in the past decade (Alikhanova and Bull, 2023; Stulina and Idirisov, 2024). Based on field observations, areas that were relatively recently afforested primarily fell under the sparse category, indicating a successful but still nascent stage of vegetation establishment and suggesting a progressive trend where plant communities begin to establish on newly formed saline soils.

Natural senescence and environmental stress also contribute to vegetation decline. Dense saxaul plantations, particularly in the far-eastern portion of the South Aral Seabed—the first areas exposed and afforested (Forestry Agency of the Ministry of Ecology Environmental Protection and Climate Change of the Republic of Uzbekistan, 2023)—now exceed 35 a of age, approaching or surpassing their typical productive lifespan (Shamsutdinova and Shamsutdinov, 2022). Given the virtually non-existent logging activity in the study area, this degradation is attributed to natural aging and environmental stress rather than anthropogenic removal. Additionally, wetland reduction along the southern shoreline, occurring at an annual rate of 7.33%, likely exacerbates stress on nearby saxaul stands, as even drought-tolerant species are highly responsive to reduced moisture availability (Liu et al., 2023).

These findings provide the first MSAVI-based decadal assessment of land cover dynamics in the South Aral Seabed, establishing critical baseline data. Overall, the landscape exhibits high volatility, where anthropogenic transformation (afforestation) is spatially extensive but constantly challenged by the dominant environmental degradation processes, including salinization and desiccation. The high rate of observed changes underscores the importance of monitoring restoration efforts and projecting future landscape trajectories as the South Aral Sea is likely approaching complete desiccation.

5.3 Study limitations

Despite the high accuracy of the produced land cover maps, several limitations should be noted.

First, cloud-free images were not always available for the required period, necessitating the use of multi-temporal mosaics that may have slightly affected image brightness and reflectance.

Additionally, MSAVI thresholds applied are season- and site-specific, valid only for summer in this region. However, summer classification reduced the risk of

misclassification caused by soil Shahzoda ALIKHANOVA et al.: Improving land cover classification in drylands...moisture variations typical of other seasons, as well as issues related to high cloud cover. The spatial resolution of Landsat 8 (30 m) also limited detection of features such as narrow collector-drainage canals and small vegetation patches observed in the field but missed in the maps. Lastly, challenging terrain and lack of access roads prevented field data collection in the far eastern part of the lakebed, and the absence of soil measurements hindered detailed soil parameter assessment, including salinity.

6 Conclusions

This study addressed critical gaps in dryland land cover mapping by evaluating the MSAVI performance and conducting a decadal analysis (2013-2023) of land cover change in the South Aral Seabed, a region frequently absent or misrepresented in global datasets. Two classification approaches were developed and compared: a MSAVI-based single-index classification and a multi-index approach integrating MSAVI with a water index (NDWI) and a salinity index (SI1) to overcome spectral confusion characteristic of extreme dryland environments.

Both approaches demonstrated clear advantages over conventional NDVI-based methods and existing global land cover products. The MSAVI-based classification achieved higher overall accuracy, while the multi-index approach enabled finer discrimination between ecologically critical classes, particularly separating salt pans from solonchak (saline) soils. Decadal analysis revealed a highly dynamic landscape, with over half the study area experiencing land cover transitions driven by rapid desiccation, wetland loss, and accelerating soil salinization, alongside localized vegetation establishment through targeted afforestation efforts.

This study provides the first comprehensive MSAVI-based land cover assessment of the South Aral Seabed, establishing a 30 m resolution baseline for one of the world's most rapidly changing dryland landscapes. The findings demonstrate that soil-adjusted vegetation indices are essential for accurate classification in drylands where conventional indices fail, and that strategic integration of multiple spectral indices with extensive field validation produces regionally appropriate results superior to global products.

The comparative classification framework developed here offers a replicable and adaptable methodology for enhanced land cover monitoring across Central Asian drylands and other arid areas facing similar challenges of sparse and patchy vegetation, high soil reflectance, and rapid environmental degradation. The insights derived from this study directly support evidence-based environmental monitoring, restoration planning, and adaptive management policies ecologically vulnerable dryland ecosystems undergoing accelerated transformation.

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Shahzoda ALIKHANOVA et al.: Improving land cover classification in drylands ...

Appendix

Table S1 List of satellite images used for land cover mapping in the South Aral Seabed Sensor Acquisition date Landsat 8 Level 2

14 June 2013

Note: Path and row numbers specify the location of each Landsat image within the Landsat Worldwide Reference System (WRS-2) grid, which is the standard system used to identify Landsat scenes on the Earth' s surface.

Table S2 Confusion matrix of single-index land cover classification using MSAVI in the South Aral Seabed in Land cover class Surface water Salt pan and solonchak Surface water Salt pan and solonchak Other barren land Sparse or distressed vegetation Dense and healthy vegetation Wetland Total Other barren Sparse or distressed vegetation Dense and healthy vegetation Wetland Total User' s accuracy Kappa coefficient Producer' s accuracy Kappa coefficient Table S3 Confusion matrix for multi-index land cover classification using MSAVI, Normalized Difference Water Index (NDWI), and Salinity Index 1 (SI1) in the South Aral Seabed in 2023 Land cover class Surface water Salt pan and solonchak Surface water Salt pan and solonchak Other barren land Sparse or dis-

tressed vegetation Dense and healthy vegetation Wetland Total Other barren
Sparse or distressed vegetation Dense and healthy vegetation Wetland Total
User' s accuracy Kappa coefficient Producer' s accuracy Kappa coefficient

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv –Machine translation. Verify with original.