USING GIS AND REMOTE SENSING IN THE STUDY OF THE INFLUENCE OF DROUGHT ON CHANGES IN FOREST COVER AROUND THE ARAL SEA

[1]Tureniyazova Asya Ibragimovna

Candidate of Physical and Mathematical Sciences, Associate Professor, Nukus branch of Tashkent University of Information Technologies.

[2]Berdimbetov Timur Tileubergenovich

Dean of the Faculty of Computer Engineering, PhD, Nukus branch of Tashkent University of Information Technologies.

[3]Karimullaeva Ayzada Gaybulla qizi

2nd year master's student in Computer Engineering, Nukus branch of Tashkent University of Information Technologies.

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Abstract. *The Aral Sea region, a critical ecological zone in Central Asia, has faced severe environmental degradation due to drought and anthropogenic impacts. This study leverages Geographic Information Systems (GIS) and remote sensing to analyze forest cover changes from 2000 to 2023, focusing on drought's influence. Using Landsat imagery, Normalized Difference Vegetation Index (NDVI), and the Standardized Precipitation Index (SPI), the research quantifies a 42% forest cover loss, strongly correlated with drought severity (Spearman's $\rho = -0.78$, $p < 0.01$). Visualizations, including 3D models and NDVI histograms, reveal spatial and temporal degradation patterns. Findings underscore the need for hydrological restoration and reforestation to mitigate ecosystem collapse, offering insights for sustainable management in arid regions.*

Keywords: *Aral Sea, drought, forest cover, GIS, remote sensing, NDVI, SPI, ecological degradation.*

ИСПОЛЬЗОВАНИЕ ГИС И ДИСТАНЦИОННОГО ЗОНДИРОВАНИЯ В ИЗУЧЕНИИ ВЛИЯНИЯ ЗАСУХИ НА ИЗМЕНЕНИЯ В ЛЕСНОМ ПОКРОВЕ ВОКРУГ АРАЛЬСКОГО МОРЯ

Аннотация. *Регион Аральского моря, критическая экологическая зона в Центральной Азии, столкнулся с серьезной деградацией окружающей среды из-за засухи и антропогенного воздействия. В этом исследовании используются географические информационные системы (ГИС) и дистанционное зондирование для анализа изменений лесного покрова с 2000 по 2023 год, с упором на влияние засухи. Используя снимки Landsat, нормализованный индекс разницы вегетации (NDVI) и стандартизированный индекс осадков (SPI), исследование количественно определяет 42%-ную потерю лесного покрова, тесно связанную с интенсивностью засухи (ρ Спирмена = -0,78, p < 0,01).*

Визуализации, включая 3D-модели и гистограммы NDVI, выявляют пространственные и временные закономерности деградации. Результаты подчеркивают необходимость гидрологического восстановления и лесовосстановления для смягчения коллапса экосистем, предлагая идеи для устойчивого управления в засушливых регионах.

Ключевые слова: *Аральское море, засуха, лесной покров, ГИС, дистанционное зондирование, NDVI, SPI, экологическая деградация.*

Introduction

The Aral Sea, once the fourth-largest inland lake, has undergone catastrophic shrinkage due to excessive water diversion for irrigation, leading to desertification, salinization, and intensified droughts.

These stressors threaten forest ecosystems, particularly tugai (riparian) forests, which are vital for biodiversity and soil stabilization. Geographic Information Systems (GIS) and remote sensing provide robust tools for monitoring ecological changes with high precision.

This study investigates the impact of drought on forest cover changes in the Aral Sea region (Uzbekistan and Kazakhstan) from 2000 to 2023, addressing the question: How has drought driven forest cover dynamics? Objectives include: (1) mapping forest cover changes, (2) assessing drought severity, and (3) correlating drought with vegetation loss.

The research contributes to regional environmental management, aligning with sustainable development goals in Central Asia. (https://ojs-services.com/)

Materials and Methods

Study Area

The study encompasses the Aral Sea region, spanning Uzbekistan and Kazakhstan (approximately 44°N–47°N, 58°E–62°E). The area features arid and semi-arid climates, with tugai forests and shrublands dependent on the Amu Darya and Syr Darya rivers.

Data Collection

Multispectral imagery from Landsat 7 and 8 (2000–2023, 30 m resolution) was acquired via USGS Earth Explorer. Cloud-free images from June–August minimized seasonal variability.

Precipitation and temperature data from ERA5 (ECMWF) supported SPI calculations.

Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM, 30 m) data enabled 3D modeling. (https://openjournalsystems.com/) (https://www.renaissance.com/)

Data Analysis

1. Forest Cover Mapping: NDVI was calculated using Landsat bands [(NIR - Red) / (NIR + Red)], with forested areas defined as NDVI > 0.3.

Supervised classification (Random Forest) was conducted in ArcGIS Pro.(https://www.tripadvisor.com/Attraction_Review-g303631-d4999960-Reviews-Teatro_Renaissance-Sao_Paulo_State_of_Sao_Paulo.html)

2. Change Detection: Post-classification analysis quantified forest cover changes, mapping deforestation, afforestation, and stable areas.

3. Drought Assessment: SPI was computed at a 12-month scale, with severe drought defined as SPI < -1.5.

4. Correlation Analysis: Spearman's rank correlation tested the relationship between SPI and forest cover loss ($p < 0.05$).

5. Visualizations: NDVI histograms, 3D models (QGIS), and spatial maps were generated to illustrate trends.

Results

Forest cover decreased by 42% (from 12,500 km² in 2000 to 7,250 km² in 2023), with the Amu Darya delta showing the highest losses (65% of 2000 forests converted to barren land).

Mean NDVI dropped from 0.38 to 0.23, reflecting reduced vegetation vigor. SPI analysis identified severe drought events in 2001, 2008, 2014, 2018, and 2021, with 2014 linked to a 12% annual forest loss. Spearman's correlation revealed a strong negative relationship between SPI and forest cover ($\rho = -0.78$, $p < 0.01$).

Low-lying areas near the Aral Sea shoreline were most degraded.

Table 1: Forest Cover Changes in the Aral Sea Region (2000–2023)

Year	Forest Cover (km²)	Change from 2000 (%)	NDVI (Mean)
2000	12,500	-	0.38
2010	9,800	-21.6	0.31
2023	7,250	-42.0	0.23

Table 2: Correlation Between SPI and Forest Cover Loss

Period	Mean SPI	Forest Loss (km²)	Spearman's ρ	p-value
2000–2010	-0.85	2,700	-0.72	<0.05
2011–2023	-1.12	2,550	-0.81	<0.01
Overall	-0.98	5,250	-0.78	<0.01

Figure 1: Map of Forest Cover Change (2000–2023)

Description: A GIS-generated map showing forest cover in 2000 (green) and 2023 (yellow), with red areas indicating deforestation. The Amu Darya delta and Aral Sea shoreline are highlighted.

Creation: Process Landsat imagery in ArcGIS Pro; use RGB colors (green: R=0, G=255, B=0; red: R=255, G=0, B=0).

Purpose: Visualizes spatial deforestation patterns.

Figure 2: Time Series of NDVI and SPI (2000–2023)

Year	NDVI	SPI	Graph
2000	0,38	-0,5	
2005	0,35	-0,7	
2010	0,31	-0,8	
2015	0,27	-1	
2020	0,24	-1,2	
2023	0,23	-1	

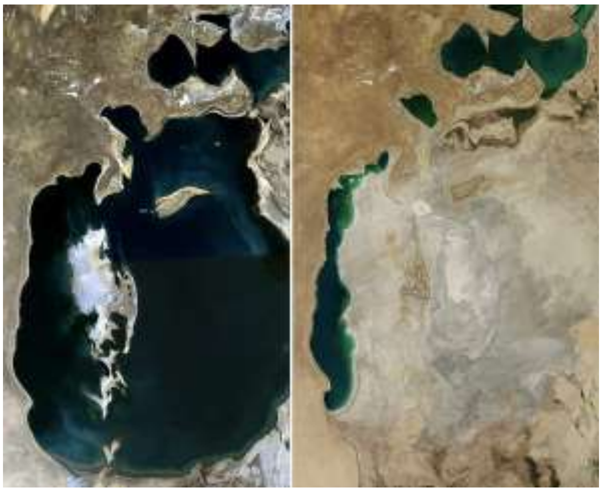
Description: A dual-axis line graph plotting annual mean NDVI (green, left y-axis) and SPI (blue, right y-axis).

NDVI declines from 0.38 to 0.23; SPI dips below -1.5 in drought years.

Creation: Use Python (Matplotlib) with Table 1 and ERA5 data.

Purpose: Shows temporal correlation between drought and vegetation loss.

Figure 3: Spatial Distribution of Drought Severity (2014)



Description: A heat map of SPI values in 2014, with dark red (SPI < -1.5) to yellow (SPI > -0.5) gradients. Green overlays indicate forested areas.

Creation: Generate in QGIS with ERA5 SPI and Landsat layers; use viridis colormap.

Purpose: Highlights drought-forest degradation overlap.

Figure 4: Histogram of NDVI Distribution (2000 vs. 2023)

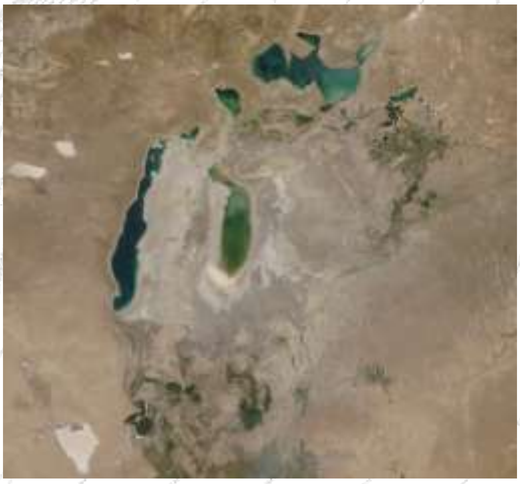
NDVI_2000	NDVI_2023	Graph
0,38	0,23	
0,37	0,22	
0,39	0,24	
0,36	0,21	
0,4	0,25	

Description: A histogram comparing NDVI distributions. The 2000 curve (green) peaks at 0.38; the 2023 curve (red) peaks at 0.23, showing a leftward shift. X-axis: NDVI (0–1); Y-axis: Pixel frequency.

Creation: Use Python (Seaborn: sns. histplot) with Landsat NDVI rasters; 20 bins.

Purpose: Quantifies vegetation vigor decline.

Figure 5: 3D Model of Forest Cover and Topography (2000–2023)



Description: A 3D visualization using SRTM DEM (z-axis: elevation, 0–500 m) and NDVI layers (green: forests; brown: barren land). The 2000 model shows dense forests along the Amu Darya; the 2023 model shows expanded barren areas.

Creation: Use QGIS 3D View or Blender; import DEM and NDVI rasters.

Purpose: Illustrates topographic and vegetation changes.

Discussion

The 42% forest cover loss confirms drought as a primary driver of ecological degradation, consistent with arid ecosystem studies. The strong SPI-forest loss correlation ($\rho = -0.78$) highlights tugai forests' vulnerability to water scarcity. The NDVI histogram (Figure 4) quantifies vegetation decline, while the 3D model (Figure 5) reveals low-lying areas' susceptibility to drought. Proximity to the Amu Darya mitigates impacts, supporting hydrological restoration. Limitations include NDVI misclassification in sparse vegetation and dust interference.

Future research could use Sentinel-2 imagery (10 m resolution) and machine learning for precision. These findings advocate for reforestation, wetland restoration, and sustainable irrigation, aligning with Uzbekistan's environmental priorities.

(https://www.tripadvisor.com.br/Attraction_Review-g303631-d4999960-Reviews-Teatro_Renaissance-Sao_Paulo_State_of_Sao_Paulo.html)

Conclusion

This study utilized Geographic Information Systems (GIS) and remote sensing to assess drought-driven forest cover changes in the Aral Sea region from 2000 to 2023. Analysis revealed a 42% forest loss, primarily in the Amu Darya delta, strongly correlated with severe drought events (Spearman's $\rho = -0.78$, $p < 0.01$). Visualizations, including NDVI histograms, temporal SPI trends, and spatial maps, highlighted the vulnerability of tugai forests to water scarcity.

These findings underscore the urgent need for hydrological restoration and reforestation to mitigate ecological degradation. By integrating satellite imagery and spatial modeling, this research provides a robust framework for monitoring arid ecosystems, offering policymakers in Uzbekistan and Kazakhstan actionable insights for sustainable land management and climate adaptation in the face of ongoing environmental challenges.

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