# Forest dynamics and afforestation efficacy in the south-western Aral Sea Basin: a multi-decadal satellite observation approach

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**Abstract.** This study analyzes the transformation of forest ecosystems in the Republic of Karakalpakstan during 2000-2024 using modern information technologies — remote sensing, geographic information systems (GIS), and artificial intelligence algorithms.

The study employs the Google Earth Engine (GEE) cloud platform, the Python programming language, QGIS, and ArcGIS Pro. Land cover classification was performed using the Random Forest algorithm on Landsat 7/8/9 and Sentinel-2 satellite imagery. Transfer matrix and intensity analysis methods were used to quantify forest-land cover transitions. Forecast maps for 2030–2040 were generated using the CA-Markov model.

Results show that tugai forests decreased by 32% and saxaul forests by 19% during 2000–2024, while saline areas expanded by 50%. Classification accuracy reached 91.3% (Kappa = 0.88). Under the BAU scenario, tugai forests are projected to decline by an additional 38% by 2040.

**Keywords:** Karakalpakstan, Remote Sensing, GEE, Random Forest, CA-Markov, Tugai forest, Saxaul

## Introduction

History of the use of satellites in forest monitoring: (Tucker, 1979) proposed the NDVI index and used it to assess vegetation density. (Hansen et al., 2013) created the first global-scale pixel-scale map of forest loss based on Landsat. (Cohen and Goward, 2004) substantiated the special role of Landsat data in environmental applications. In the field of Google Earth Engine, (Gorelick et al., 2017) published a key article describing the architecture and capabilities of the platform. There are many special works related to the monitoring of tree coverage using GEE: (Bullock et al., 2020) methods for processing historical landscape series; (Potapov et al., 2021) presented the results of mapping the forest cover on a global scale with a resolution of 10 m. In the field of machine learning methods, (Belgiu and Drăguţ, 2016) thoroughly reviewed the application of the Random Forest algorithm in remote sensing and analyzed it in comparison with SVMs and neural networks. The results showed that the Random Forest classification prevails in many cases in terms of stability and ease of adjustment of hyperparameters. The transfer matrix methodology was developed in the works of (Pontius and Millones, 2011), (Aldwaik and Pontius, 2012). They introduced the concepts of quantitative disagreement (quantity disagreement) and allocation disagreement (allocation disagreement) and developed a three-level hierarchical system of intensity analysis. This methodology is currently recognized as a standard analytical tool in landscape

ecology. Special research on Central Asian forests: (Lioubimtseva and Henebry, 2009) conducted a comprehensive study of climate change and land degradation in Central Asia. (Le and Kappas, 2016) analyzed the forest cover in Kazakhstan based on Landsat and MODIS. For the Amu Darya delta, (Nezlin, 2016) modeled hydrological and ecological relationships.

To address these research gaps, this study aims to comprehensively analyze the transformation of the forest cover of the Republic of Karakalpakstan between 2000 and 2024 using multi-source satellite remote sensing data, evaluate the ecological efficacy of newly established green plantations and build a spatial forecast model for 2040 using Cloud Computing (GEE), Python-based Machine-Learning, and land transition matrices.

## Materials and methods

### 2.1 Study Area

The study was conducted across the degraded forest stands, riparian tugai ecosystems, saxaul plantations, and adjacent hyper-arid zones within the Republic of Karakalpakstan, south-western Aral Sea Basin (41.5°–45.5 ° N and 55.5°–62.5° E). The region experiences an extreme continental climate characterized by severe precipitation deficits (annual average ranging between 50 mm and 120 mm), high atmospheric vapor pressure deficits, and summer temperatures frequently exceeding 40 °C. The ecological equilibrium in the lower reaches of the Amu Darya delta is strongly coupled with hydrological inputs; previous studies indicate that a 50 % reduction in discharge leads to a corresponding 60-70% loss of natural riparian tugai canopy coverage (Crétaux and Letolle, 2019; Micklin, 2016). Over recent decades, intensified soil salinization and shifting dust storm patterns have disrupted natural forest succession, necessitating rigorous spatial evaluation of forest condition and greening interventions.

### 2.2 Data collection & Satellite Datasets

To capture multi-decadal landscape dynamics and quantify forest cover transformations, multi-sensor spatial imagery spanning 2000–2024 was extracted and processed using cloud-based infrastructure (Google Earth Engine). Primary observational datasets were derived from the Landsat series (Landsat 7 ETM+, Landsat 8 OLI, and Landsat 9 OLI-2) alongside Sentinel-2 MSI and MODIS time-series products.

**Landsat 7 ETM+ (2000–2012):** Utilized for baseline spatial monitoring at 30 m spatial resolution across 8 spectral bands. Scan Line Corrector (SLC-off) data gaps post-2003 were restored using the USGS standard focal gap-filling algorithm.

**Landsat 8 OLI & Landsat 9 OLI-2 (2013–2024):** Processed for mid-to-recent epoch monitoring at 30m spatial resolution (100m thermal). Enhanced signal-to-noise performance provided consistent vegetation canopy measurements.

**Sentinel-2 MSI (2015–2024):** Integrated at 10 m (visible/NIR) and 2m (red-edge/SWIR) resolutions to validate fine-scale afforestation boundaries and canopy structure.

**MODIS (Terra/Aqua):** MOD13A2 (16-day NDVI at 1 km) and MOD44B (Vegetation Continuous Fields at 250m) were ingested for continuous seasonal and trend validation.

**Auxiliary Geospatial Data:** Topographic correction was implemented using the 30m SRTM Digital Elevation Model (DEM). Land cadastre vector layers (2000, 2010, 2020), FAO/IIASA GAEZ soil characteristics, and ERA5 reanalysis climate data were integrated to model ecological suitability drivers.

**2.3. Machine Learning Classification and Accuracy Assessment**

Land cover mapping was executed using the Random Forest (RF) ensemble classifier (Breiman, 2001). Hyperparameters were optimized via 10-fold cross-validation using GridSearchCV (n_estimators = 200, max_depth = None, min_samples_leaf = 2). The classification scheme defined primary land-cover categories across Karakalpakstan based on spectral and ecohydrological characteristics.

**Table 1.** Land Cover Classification Scheme and Spectral NDVI Thresholds

| Class ID | Land Cover Category | NDVI Range | Ecohydrological Description |
|---|---|---|---|
| 1 | Riparian Tugai Forest | 0.40–0.75 | Dense poplar (Populus euphratica), willow (Salix spp.), and Tamarix trees along riverbanks |
| 2 | Saxaul Forest (Haloxylon spp.) | 0.12–0.35 | Black and white saxaul desert woodlands and artificial plantations |
| 3 | Sparse/Desert vegetation | 0.05–0.18 | Annual grasses, drought-resistant desert shrubs, and halophytic herbs |
| 4 | Irrigated cropland | 0.30–0.65 | Agricultural lands including cotton, wheat, rice, and melon crops |
| 5 | Saline land/ Bare soil | 0.02–0.10 | Degraded pastures, abandoned agricultural lands, and open soil surfaces |



## Results

**4.1. Results of the transfer matrix interpretation. Analysis** of the period 2000-2010. The results of the transfer matrix and intensity analysis calculated for this period are as follows. Average annual intensity of change U = 0.82%/year. Intensity of tugai loss: 1.43%/year (1.74-fold higher than U – active loss). Intensity of saxaul forest loss: 0.71%/year (0.87-fold lower than U – relatively stable). Growth intensity of saline soils: 2.31%/year (2.82-fold higher than U – active growth). At the level of transition: transition from forest to saline soil 3.18 times, transition from forest to sand 2.41 times higher than the expected random value.

Analysis of the period 2010-2024. Annual average intensity U = 1.14%/year (increased by 39% compared to the first period). Intensity of tugai loss: 2.07%/year (1.82 times). Intensity of saxaul forest loss: 1.01%/year (0.89 times). Additional result: 5,200 hectares of reforested land between 2010 and 2024 consist of irrigated crops and sparse vegetation that have passed into the “forest” category.

***Table 2.*** Results of the intensity analysis for the period 2010-2024 (U=1.14%/year)

| Category | Gain (ha) | Loss (ha) | Net (ha) | Loss %/year | Gain %/year | Loss active? | Gain active? |
|---|---|---|---|---|---|---|---|
| Tugai forest | 5 200 | -24 800 | -19 600 | 2.07 | 0.44 | Yes | No |
| Saxaul forest | 1 800 | -15 200 | -13 400 | 1.01 | 0.11 | No | No |
| Sparse vegetation | 9 400 | -39 800 | -30 400 | 0.68 | 0.19 | No | No |
| Desert/sandy | 28 100 | -3 800 | +24 300 | 0.20 | 0.31 | No | No |
| Saline soil | 27 600 | -4 200 | +23 400 | 0.15 | 2.93 | No | Yes |
| Water body | 200 | -5 100 | -4 900 | 4.22 | 0.10 | Yes | No |


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### 4.2 CA-Markov prediction results

Model validation. Based on the 2000-2010 transition probability matrix, the 2020 map was forecasted and compared with the actual map: Total accuracy OA = 81.4%, Kappa = 0.76, Forest forecast accuracy = 78.2%, Salt marsh forecast accuracy = 83.1%. This indicates that the Markov process forecast is satisfactory for this region. Forecast for 2030-2040. The forecast for the three scenarios yielded the following results:

**Table 3.** CA-Markov forecasting results – 2030 and 2040

| Scenario | **Description** | **Tugai 2030 (ha)** | **Tugai 2040 (ha)** | **Saxaul 2040 (ha)** | **Solonchak 2040 (ha)** |
|---|---|---|---|---|---|
| BAU | The current trend will continue | 75 400 | 58 200 | 255 000 | 589 000 |
| Optimistic | Reforestation + improved water distribution | 88 600 | 82 400 | 305 000 | 460 000 |
| Complex | Water-saving technology +protection +repair +monitoring | 94 600 | 97 200 | 340 000 | 400 000 |

### Conclusions and recommendations

**General Trend:** Between 2000 and 2024 in Karakalpakstan, tugai forests decreased by 32.1% (138,200 -> 93,800 ha), saxaul forests decreased by 19.0%

(420,000 -> 340,000 ha), water bodies shrank by 67.9%, and saline areas expanded by 50.0% ($p<0.001$).

**Methodology:** Using Random Forest on Google Earth Engine yielded 91.3% accuracy and a 0.88 Kappa coefficient. Tugai loss intensity was U = 1.14%/year.

**Mechanism:** The transition from tugai to saline soil increased 3.18-fold, driven by the desiccation of the Aral Sea rather than sudden local factors (r = 0.89 correlation between NDVI and water consumption).

**Forecasting:** Under the BAU scenario for 2040 using the CA-Markov model, tugai areas will decrease to 58,200 ha (-37.9%) unless active conservation measures (+3.6% increase) are implemented.

**IT Contribution:** Developed an open-source pipeline (Python + Web Dashboard) for automated remote sensing and tugai monitoring in Uzbekistan.

**Hypothesis Validation:** Confirmed that tugai transformation in Karakalpakstan is systematic and progressive, perfectly modeled via Markov chain analysis.

**Recommendations**

1. **State-Level Structures:** Conclude an interstate water-allocation agreement (ASBP-4 framework) ensuring an ecological minimum of 5-7 km3/year for Karakalpakstan's tugai ecosystems.
2. **Reforestation Program:** Adopt a 2025–2035 program covering 50,000 ha (planting poplar and willow), plant 5,000 ha annually, and introduce subsidies for local elm nurseries.
3. **Monitoring System:** Implement an automated GEE-based tugai monitoring system utilizing the dissertation's software, making annual tugai status reports mandatory.
4. **Legislation:** Strengthen the Forestry Code regarding saxaul and tugai protection, increase illegal logging penalties 5-fold, and equip forest inspection with drones and GPS units.

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