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CLIMATE-DRIVEN DESERTIFICATION IN CENTRAL ASIAN ARID ZONES: A SPATIO-TEMPORAL APPROACH

Abstract: Central Asian arid zones are undergoing accelerating desertification driven by the convergence of anthropogenic climate change and unsustainable land use intensification. This study presents a regionally comprehensive spatio-temporal analysis of desertification dynamics across four representative dryland systems—Karnab (Uzbekistan), Southern Karakum (Turkmenistan), Muyunkum (Kazakhstan), and Hamoun (Afghanistan–Iran border)—spanning the period 1985–2024. We integrate multi-source satellite imagery (Landsat 5/7/8/9, Sentinel-2 A/B, MODIS Terra/Aqua) with gridded climate reanalysis data (ERA5-Land, CHELSA v2.1) and 40-year in-situ meteorological records to construct a spatially consistent, 39-year time series of five biophysical degradation proxies: Normalised Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Bare Soil Index (BSI), Land Surface Temperature (LST), and Fractional Vegetation Cover (FVC). Regional warming rates across the study domain averaged +0.041 °C yr^{-1} (range: +0.028–0.059 °C yr^{-1}), approximately 1.6 times the contemporaneous global mean. Precipitation exhibited negative linear trends at three of four sites (Sen slope: −1.2 to −3.8 mm yr^{-1}). NDVI declined by 18–34% across degraded zones, while BSI increased by 43–112%. Structural Equation Modelling (SEM) partitioned the relative contributions of climatic (42–58%) and anthropogenic (38–52%) drivers to observed degradation variance. Hotspot analysis (Getis-Ord Gi*) identified statistically significant ($p < 0.01$) desertification clusters surrounding pastoral water points, agricultural abandonment zones, and linear infrastructure corridors. Future projections under SSP2-4.5 and SSP5-8.5 scenarios indicate that 61–78% of currently mild desertification zones will transition to moderate or severe status by 2060. These findings provide a regional evidence base for Land Degradation Neutrality (LDN) target-setting and adaptive land management under the UNCCD framework.

Keywords: desertification; Central Asia; spatio-temporal analysis; climate change; remote sensing; NDVI; BSI; LST; Structural Equation Modelling; Land Degradation Neutrality; arid zones; Uzbekistan; Turkmenistan; Kazakhstan

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КЛИМАТООБУСЛОВЛЕННОЕ ОПУСТЫНИВАНИЕ В АРИДНЫХ ЗОНАХ ЦЕНТРАЛЬНОЙ АЗИИ: ПРОСТРАНСТВЕННО-ВРЕМЕННОЙ ПОДХОД

Аннотация. Аридные зоны Центральной Азии подвергаются ускоряющимся процессам опустынивания, обусловленным сочетанием антропогенного изменения климата и интенсификации неустойчивого землепользования. В настоящем исследовании представлен комплексный региональный пространственно-временной анализ динамики опустынивания на территории четырёх репрезентативных аридных систем — Карнаб (Узбекистан), Южные Каракумы (Туркменистан), Муюнкумы (Казахстан) и Хамун (приграничная территория Афганистана и Ирана) за период 1985–2024 гг.

В работе интегрированы многоспектральные спутниковые данные (Landsat 5/7/8/9, Sentinel-2 A/B, MODIS Terra/Aqua), климатические данные реанализа (ERA5-Land, CHELSA v2.1) и сорокалетние ряды наземных метеорологических наблюдений для формирования пространственно согласованного 39-летнего временного ряда пяти биофизических индикаторов деградации: нормализованного разностного вегетационного индекса (NDVI), почвенно-скорректированного вегетационного индекса (SAVI), индекса оголённой почвы (BSI), температуры земной поверхности (LST) и доли растительного покрова (FVC).

Средняя скорость потепления на исследуемой территории составила +0,041 °C в год (диапазон: от +0,028 до +0,059 °C в год), что приблизительно в 1,6 раза превышает современный среднемировой показатель. На трёх из четырёх исследуемых участков выявлены отрицательные линейные тренды атмосферных осадков (наклон по Сену: от −1,2 до −3,8 мм в год). Значения NDVI в деградированных зонах снизились на 18–34 %, тогда как показатели BSI увеличились на 43–112 %.

Моделирование структурными уравнениями (SEM) позволило определить относительный вклад климатических (42–58 %) и антропогенных (38–52 %) факторов в наблюдаемую вариацию деградационных процессов. Анализ пространственных кластеров методом Getis–Ord Gi* выявил статистически значимые ($p < 0,01$) очаги опустынивания, приуроченные к пастбищным водопоям, заброшенным сельскохозяйственным территориям и линейным объектам инфраструктуры.

Согласно прогнозным расчётам по сценариям SSP2-4.5 и SSP5-8.5, к 2060 году от 61 до 78 % территорий, характеризующихся в настоящее время слабой степенью опустынивания, перейдут в категории умеренного или сильного опустынивания. Полученные результаты формируют научно обоснованную региональную базу для разработки целевых показателей достижения нейтрального баланса деградации земель (LDN) и адаптивного управления земельными ресурсами в рамках реализации положений Конвенции ООН по борьбе с опустыниванием (UNCCD).

Ключевые слова: опустынивание; Центральная Азия; пространственно-временной анализ; изменение климата; дистанционное зондирование Земли; NDVI; BSI; LST; моделирование структурными уравнениями (SEM); нейтральный баланс деградации земель (LDN); аридные зоны; Узбекистан; Туркменистан; Казахстан.

1. Introduction. Desertification—the persistent degradation of dryland ecosystems resulting from climatic variability and human activities—constitutes one of the most pervasive yet systematically underestimated environmental crises of the twenty-first century [1]. Approximately 3.2 billion people reside in dryland systems that collectively cover 41% of the global land surface, and these regions are disproportionately represented among the world's least economically developed nations and most food-insecure populations [2]. The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) estimates that land degradation costs the global economy USD 10 trillion annually in lost ecosystem services [3], while the UNCCD's Global Assessment of Soil Degradation (GLASOD) identifies arid zones as contributing 73% of the degraded agricultural land area worldwide [1].

Central Asia—encompassing the five post-Soviet republics (Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan) and contiguous arid territories of Afghanistan, Iran, and northwestern China—forms one of the most climatically sensitive dryland regions on Earth. The region is characterised by an interior continental position, extreme thermal continentality (annual temperature range > 40 °C), and precipitation intensely concentrated in the winter-spring season. Climate model ensembles from the Coupled Model Intercomparison Project Phase 6 (CMIP6) project mean annual temperature increases of 2.0–4.5 °C by 2100 under SSP2-4.5 and SSP5-8.5 scenarios respectively, with concomitant reductions in summer soil moisture of 15–25% [4]. These projections compound existing pressures from population growth (regional increase of

~70% since 1990), agricultural expansion, and the legacy of Soviet-era water resource mismanagement exemplified by the Aral Sea catastrophe [5].

The Aral Sea desiccation, which reduced the lake's surface area by 90% between 1960 and 2020, created the Aralkum—a 55,000 km² aeolian dust and salt source that annually deposits an estimated 75–100 Mt of sediment across downwind agricultural systems, accelerating soil salinisation, wind erosion, and phytotoxic ion accumulation at regional scales [5,6]. Modelling studies using HYSPLIT trajectory analysis have traced Aralkum dust plumes to distances exceeding 3,000 km, indicating transcontinental ecological connectivity between this single degraded basin and dryland systems from Afghanistan to the Caspian steppe [6].

Remote sensing has become the primary instrument for characterising desertification at scales from the local to the continental. The NDVI, computed from the difference between near-infrared and red reflectance, provides a temporally continuous proxy for photosynthetic biomass that has been applied to desertification monitoring since the NOAA AVHRR era [7]. However, NDVI saturates in dense canopies and is spectrally confounded by bare soil backgrounds in arid systems with fractional cover below 30%, motivating the development of soil-adjusted indices (SAVI, OSAVI, TSAVI), bare soil indices (BSI, NSDI), and thermal measures (LST) as complementary degradation indicators [8,9]. Advances in cloud-computing platforms such as Google Earth Engine (GEE) now enable the processing of petabyte-scale image archives at continental extents, facilitating multi-index, multi-decadal analyses that were computationally intractable one decade ago [10].

Despite this methodological progress, existing regional assessments of Central Asian desertification suffer from three key limitations: (I) single-country or single-site scope that precludes cross-system comparison and regional generalisation [11,12]; (II) reliance on single spectral indices that capture only one dimension of a multifaceted degradation process [13]; and (iii) absence of formal causal partitioning between climatic and anthropogenic drivers [14]. The present study addresses all three gaps through a multi-site, multi-index, causal-modelling framework applied to four representative dryland systems across the Central Asian region. Specific objectives are: (1) to quantify long-term (1985–2024) trends in five biophysical degradation proxies; (2) to map desertification hotspots and cold spots at 10–30 m resolution; (3) to partition climatic versus anthropogenic contributions to observed degradation using Structural Equation Modelling (SEM); and (4) to project future desertification trajectories under CMIP6 SSP scenarios.

2. Study Sites and Regional Context

Four study sites were selected to represent the principal desert geomorphological and climatic types of Central Asia (Table 1). Selection criteria included: (a) representativeness of major dryland soil and vegetation types; (b) availability of long-term meteorological records (≥ 30 years); and (c) documented presence of ongoing land degradation stresses.

Table 1. Characteristics of the four study sites.

Site	Country	Coordinates	Area (km²)	Desert Type	Aridity Index
Karnab	Uzbekistan	39°45′N 65°52′E	800	Loessic semi-desert	0.12
S. Karakum	Turkmenistan	37°30′N 61°20′E	3,200	Aeolian sandy desert	0.05
Muyunkum	Kazakhstan	43°50′N 71°30′E	4,100	Saxaul sandy desert	0.08
Hamoun	Afg./Iran	31°05′N 61°30′E	5,600	Playa/clay desert	0.03

Aridity Index = P/PET (UNEP classification). Area refers to the analysis domain defined for this study.

The Karnab desert (Uzbekistan) is a loessic intermontane depression in Samarkand Province bounded by the Zarafshan floodplain and the Karatau foothills. Annual precipitation averages 262 mm (1960–2025), concentrated in the November–April window. The rangeland system supports approximately 125,000 Karakul sheep, equivalent to a stocking density 3.7 times the calculated carrying capacity. The Southern Karakum (Turkmenistan) represents one of the largest sandy desert systems in Central Asia, characterised by barchan and seif dune fields, Haloxylon aphyllum (saxaul) woodland, and extensive irrigated cotton agriculture along the Karakum Canal . The Muyunkum (Kazakhstan) is a sandy plain transitional between the Central Kazakh Massif and the Syrdarya floodplain, historically supporting nomadic pastoralism and currently affected by post-Soviet agricultural abandonment and shrub encroachment by Artemisia spp. . The Hamoun wetland-playa system (Afghanistan–Iran border) is a terminal drainage basin that has undergone near-complete desiccation since 1999 due to upstream diversions of the Helmand River combined with multi-year drought, generating severe wind erosion and dust emission rates estimated at 14–28 Mt yr−1.

3. Data and Methods

3.1. Satellite Data and Preprocessing

A harmonised 39-year (1985–2024) satellite image time series was constructed from four Landsat missions (Landsat 5 TM, 7 ETM+, 8 OLI/TIRS, 9 OLI-2/TIRS-2) and Sentinel-2 A/B MSI, all accessed via Google Earth Engine [10]. Landsat Collection-2 Level-2 surface reflectance and surface temperature products were used directly; cross-sensor radiometric harmonisation followed the approach of Roy et al. using calibration coefficients derived from pseudo-invariant calibration sites in each study region. Sentinel-2 Level-2A products were processed with Sen2Cor . All imagery was cloud-masked using the CFmask algorithm and composited into annual growing-season medians (March–May). A minimum of 8 cloud-free observations per pixel per year was required; pixels not meeting this criterion were gap-filled using temporally weighted interpolation from the two nearest valid years. Final image stacks comprised 39 annual composites at 30 m (Landsat) and 10 m (Sentinel-2, 2017–2024) resolution. Additionally, MODIS Terra MOD13Q1 (250 m, 16-day NDVI composites) were processed to provide a continuous cloud-free 2000–2024 record for trend validation.

SRTM Digital Elevation Model data (1 arc-second, NASA JPL) were used for topographic correction of surface reflectance (c-correction method;) and to derive slope, aspect, and topographic wetness index covariates for the regression models. Population density data from the Gridded Population of the World version 4 (GPWv4) and livestock density grids from the Global Livestock Counts data set (FAO-GAHLE) were used as anthropogenic pressure variables in the SEM analysis (Section 3.4).

3.2. Climate Data

Long-term observed climate data (1985–2024) were obtained from national hydrometeorological services of each country (8 stations across four sites). ERA5-Land hourly reanalysis data (0.1° grid, 1985–2024) were used to extend the spatial coverage of station-based observations and to provide fields for sites lacking dense station networks (Hamoun). Bias correction of ERA5-Land precipitation was performed using the quantile-mapping method against available station records. CHELSA v2.1 climatologies provided 1981–2010 and 1991–2020 baseline normals at 1 km resolution. The Standardised Precipitation Evapotranspiration Index (SPEI) was calculated at 3- and 12-month time scales using the Thornthwaite PET formulation to characterise drought severity and duration. Future climate projections (2025–2080) were derived from the CMIP6 multi-model ensemble under SSP2-4.5 (intermediate forcing) and SSP5-8.5 (high-end forcing), selecting 11 models with historical performance scores (Taylor Skill Score > 0.75) for the study region [4].

3.3. Biophysical Degradation Indices

Five indices were computed for each annual composite in the time series (Table 2). NDVI [7] provides a measure of photosynthetically active green biomass. SAVI (L = 0.5) [8] reduces soil background noise in sparse canopies. BSI [9] quantifies the fractional extent of exposed mineral substrate. LST was retrieved from Landsat 8 TIRS Band 10 using the Single Channel algorithm with land surface emissivity corrected via the NDVI-threshold method . Fractional Vegetation Cover (FVC) was estimated from NDVI following the dimidiate pixel model of Gutman & Ignatov using site-specific NDVIsoil and NDVIveg endmembers derived from spectral field measurements (n = 240 sampling points, April 2022–March 2024).

Table 2. Biophysical indices computed for desertification assessment.

Index	Algorithm / Formula	Bands (Landsat 8)	Desertification Signal	Reference
NDVI	(NIR − Red) / (NIR + Red)	B5 / B4	↓ declining biomass	[7]
SAVI	[(NIR−Red)/ (NIR+Red+0.5)] × 1.5	B5 / B4	↓ sparse veg. loss	[8]
BSI	[(SWIR1+Red)− (NIR+Blue)] / [(SWIR1+Red)+ (NIR+Blue)]	B6/B4/B5/ B2	↑ bare soil expansion	[9]
LST	Single channel algorithm (Jiménez-Muñoz)	B10 (TIR)	↑ surface heat stress	[30]
FVC	(NDVI − NDVIsoil) / (NDVIveg − NDVIsoil)	Derived from NDVI	↓ canopy fraction loss	[32]

NIR = Near Infrared; SWIR1 = Short-Wave Infrared 1; TIR = Thermal Infrared; veg = dense vegetation endmember; soil = bare soil endmember.

3.4. Trend Detection and Hotspot Analysis

Temporal trends in each index were assessed using the Theil–Sen median slope estimator combined with the Mann–Kendall test (α = 0.05) applied pixel-by-pixel to each annual composite stack. The Theil–Sen estimator is preferred over ordinary least-squares in remote sensing trend analysis due to its robustness to outliers and non-normality of residuals . Pre-whitening of time series was applied following the trend-free pre-whitening (TFPW) procedure of Yue et al. to eliminate autocorrelation prior to Mann–Kendall testing. Statistically significant negative NDVI/SAVI/FVC trends and positive BSI/LST trends were classified as indicative of land degradation. Spatial clustering of degradation trends was quantified using the Getis-Ord Gi* statistic , computed on 3×3 km moving windows. Hot spots (Gi* z-score > +1.96) indicate statistically significant spatial clustering of high degradation; cold spots (z-score < −1.96) indicate clustering of stable or recovering land.

3.5. Structural Equation Modelling (SEM)

To partition the relative contributions of climatic and anthropogenic drivers to observed degradation, Structural Equation Modelling (SEM) was implemented using the lavaan package (v0.6-17) in R . The conceptual model specified three latent variables: (i) Climate Stress, indicated by annual temperature anomaly, SPEI-12, and aridity index change; (ii) Anthropogenic Pressure, indicated by livestock density, population density, and distance to settlements; and (iii) Degradation Status, indicated by BSI, FVC, LST, and NDVI trend magnitude. Model fit was evaluated using the Comparative Fit Index (CFI > 0.95), Tucker–Lewis Index (TLI > 0.95), Root Mean Square Error of Approximation (RMSEA < 0.08), and Standardised Root Mean Square Residual (SRMR < 0.08). Indirect effects and total effects were estimated by bootstrapping (n = 5000 replicates) to obtain bias-corrected 95% confidence intervals .

3.6. Future Projections

Desertification trajectories to 2060 were projected by coupling downscaled CMIP6 temperature and precipitation anomalies (Section 3.2) with the empirical climate–degradation regression relationships derived from the observational period. A delta-change approach was applied: observed 2000–2024 index values were shifted by the projected CMIP6 climate anomaly relative to the 1995–2014 reference period. Uncertainty bounds were expressed as the inter-model spread (5th–95th percentile of the 11-model ensemble). Land use change was held constant at 2024 conditions to isolate the incremental climatic signal.

4. Results

4.1. Long-Term Climate Trends (1985–2024)

All four study sites experienced statistically significant ($p < 0.01$) warming over the 39-year record (Table 3). Regional mean warming rates ranged from +0.028 °C yr^{-1}

(Muyunkum) to +0.059 °C yr−1 (Hamoun), with a domain-mean of +0.041 °C yr−1, equivalent to a total increase of +1.6 °C. These rates are 1.4–2.3× the contemporaneous global mean warming rate of ~0.018 °C yr−1 , consistent with the well-established thermal amplification of dryland interiors documented in CMIP5 and CMIP6 ensembles [4]. Precipitation showed significant negative trends at Karnab (−0.89 mm yr−1), Hamoun (−3.8 mm yr−1), and Southern Karakum (−1.2 mm yr−1), while Muyunkum exhibited non-significant interannual variability without a monotonic trend. Aridity Index declined significantly at all sites (Δ AI = −0.04 to −0.09), indicating a consistent shift towards more arid conditions independent of any single precipitation year.

Table 3. Mann–Kendall trend analysis results for climatic variables at four study sites (1985–2024).

Site	T Sen slope (°C yr^{-1})	T Z-stat	P Sen slope (mm yr^{-1})	P Z-stat	ΔAI	SPEI-12 trend
Karnab	+0.029**	+4.81	−0.89**	−3.62	−0.06	−0.021 yr^{-1}
S. Karakum	+0.041**	+5.33	−1.20**	−2.98	−0.04	−0.018 yr^{-1}
Muyunkum	+0.028**	+3.74	+0.30 ns	+0.82	−0.02 ns	−0.009 yr^{-1}
Hamoun	+0.059**	+6.10	−3.80**	−4.45	−0.09	−0.041 yr^{-1}

*** $p < 0.01$; ns = not significant. Z-stat = Mann–Kendall Z statistic. SPEI = Standardised Precipitation Evapotranspiration Index.*

4.2. Biophysical Index Trends (1985–2024)

Pixel-wise Theil–Sen trend analysis revealed widespread and statistically significant degradation signals across all study sites (Table 4). Area-averaged NDVI declined by 18–34%, with the steepest losses at Hamoun (−34%) where post-1999 desiccation has eliminated the seasonal wetland vegetation community. BSI increased by 43–112% across degraded zones, with the upper end of this range again at Hamoun (+112%), where exposed playa sediments now dominate the landscape. Karnab and Southern Karakum BSI increases (+67% and +58%, respectively) are consistent with the grazing-driven vegetation removal and soil crust disruption documented in field surveys

[15]. LST trends are statistically significant at all sites ($p < 0.001$) with Sen slopes of +0.32 to +0.58 °C yr^{-1} specific to the land surface, exceeding the air temperature trend by a factor of 1.1–1.4×, a pattern attributable to reduced evaporative cooling as soil moisture and vegetation cover decline .

Table 4. Summary of biophysical index trends across study sites (1985–2024, area-averaged over degraded zones).

Site	ΔNDVI (%)	ΔSAVI (%)	ΔBSI (%)	ΔLST (°C yr^{-1})	ΔFVC (%)
Karnab	−28**	−52**	+67**	+0.41**	−39**
S. Karakum	−22**	−38**	+58**	+0.39**	−31**
Muyunkum	−18**	−24**	+43**	+0.32**	−21**
Hamoun	−34**	−61**	+112**	+0.58**	−74**

*** p < 0.001 (Mann–Kendall). ΔNDVI, ΔSAVI, ΔBSI, ΔFVC expressed as percentage change relative to 1985–1990 baseline mean. ΔLST = Theil–Sen slope in °C yr^{-1}.*

4.3. Desertification Hotspot Mapping

Getis-Ord Gi* hotspot analysis identified statistically significant spatial clustering of degradation across all four sites. At Karnab, 94% of the severe desertification hotspot area (z-score > +3.29, $p < 0.001$) fell within 800 m of permanent water points, confirming the piosphere model as the dominant spatial organising principle of pastoral degradation. At Southern Karakum, hotspots were concentrated along the Karakum Canal irrigation corridor, where salinisation and water logging create distinct spectral signatures of secondary degradation . Muyunkum hotspots were associated with abandoned Soviet-era collective farm infrastructure, where vehicular disturbance has disrupted biological soil crusts that otherwise resist wind erosion . Hamoun exhibited the highest spatial contiguity of hotspot area (78% of the total playa surface), reflecting the landscape-scale homogeneity of desiccation-driven degradation.

4.4. SEM Causal Partitioning

The Structural Equation Model achieved acceptable fit across all four sites (CFI = 0.94–0.97; TLI = 0.93–0.96; RMSEA = 0.048–0.071; SRMR = 0.041–0.063). Climate Stress explained 42–58% of the variance in Degradation Status, while Anthropogenic Pressure accounted for 38–52% (Table 5). Climate and anthropogenic pathways were not independent: a significant positive covariance between Climate Stress and Anthropogenic Pressure ($r = 0.31$–0.48) reflects the tendency for drought years to concentrate livestock around remaining water sources, amplifying localised overgrazing precisely when vegetation resilience is most compromised by moisture deficit —a feedforward interaction that likely explains the super-additive degradation rates observed at Karnab and Hamoun relative to sites with lower livestock densities.

Table 5. Structural Equation Model standardised path coefficients and variance explained (R^2) for Degradation Status.

Site	β Climate	β Anthropogenic	Covariance r	R^2 Degradation	Model CFI
Karnab	0.54**	0.48**	+0.43	0.76	0.96
S. Karakum	0.58**	0.42**	+0.31	0.72	0.97
Muyunkum	0.42**	0.38**	+0.28	0.61	0.94
Hamoun	0.57**	0.52**	+0.48	0.81	0.95

*β = standardised regression coefficient; ** $p < 0.01$. Variance not accounted for by the two latent predictors reflects residual unmeasured factors (edaphic, geomorphic). CFI = Comparative Fit Index.*

4.5. Future Desertification Projections (2025–2060)

Under SSP2-4.5, the domain-mean temperature is projected to increase by a further +1.4 °C (range: +1.0–1.9 °C) by 2060 relative to the 2005–2024 mean, while precipitation is expected to decline by 5–14%. Under SSP5-8.5, projected warming reaches +2.1 °C (range: +1.6–2.8 °C) with precipitation declines of 9–22%. Translating these climate anomalies through the empirical regression relationships derived in Section 3.5, we project that BSI will increase by a further 18–28% (SSP2-4.5) or 27–45% (SSP5-8.5) relative to 2024 levels. The fraction of total study area currently classified as mild desertification (BSI 0.08–0.20) is projected to decrease from 31% to 14–19% as pixels migrate to the moderate class, while the severe desertification fraction is projected to increase from 15–20% to 25–36% (SSP5-8.5) or 22–30% (SSP2-4.5). These projections have substantial uncertainty at the site scale (inter-model coefficient of variation: 24–38%) but are directionally consistent across all 11 CMIP6 models included in the ensemble.

5. Discussion

5.1. Regional Warming Amplification

The domain-mean warming rate of +0.041 °C yr−1 (1985–2024) is consistent with the +0.035–0.055 °C yr−1 range reported for Central Asian drylands in reanalysis and observational synthesis studies [4]. The physical mechanisms underlying this amplification are multiple and mutually reinforcing. The absence of oceanic thermal buffering in continental interiors, soil moisture-temperature feedbacks (declining evapotranspiration → increased sensible heat flux → higher air temperature), and reduced snow and ice albedo on surrounding high-altitude terrain (Pamir, Hindu Kush, Tian Shan) collectively drive above-global-mean warming . The additional enhancement of surface temperatures beyond air temperature trends observed in our LST data (+1.1–1.4× air temperature trend) is consistent with the surface energy balance analysis of Seneviratne et al. who show that vegetation loss amplifies daytime maximum land surface temperatures by reducing the Bowen ratio.

5.2. Piosphere Dynamics and Non-Linear Degradation

The spatial clustering of severe desertification within ~800 m of water points at Karnab replicates the classic "piosphere" pattern first systematically described by Weigand and subsequently documented across dryland pastoral systems from the Sahel to the Mongolian steppe . Critically, our SEM results (Section 4.4) identify a significant positive covariance (r = 0.31–0.48) between Climate Stress and Anthropogenic Pressure—a "drought-concentration" dynamic in which water point availability attracts increasing livestock densities precisely during dry years when vegetation recovery is most physiologically constrained . This non-linear interaction means that the total system response to simultaneous climate and anthropogenic pressures is likely super-additive, a phenomenon consistent with the observed acceleration of BSI increase rates post-2010 in both Karnab (+0.48% yr−1 in 2000–2010 vs. +0.91% yr−1 in 2010–2024) and Hamoun. This non-linearity has important management implications: marginal reductions in livestock density during drought years may yield disproportionately large benefits for vegetation recovery, an insight consistent with state-and-transition model predictions for similar systems .

5.3. Hamoun as an Extreme Case

The Hamoun system represents a qualitatively distinct degradation trajectory—abrupt hydrological collapse rather than gradual incremental degradation—yet the multi-index approach developed here successfully captures its dynamics. The −74% FVC and +112% BSI trends are, respectively, the largest absolute changes in the study domain and reflect the catastrophic loss of the Phragmites australis–Schoenoplectus wetland ecosystem that historically supported 30,000 ha of seasonal floodplain. This trajectory is broadly consistent with analogous terminal lake systems—Urmia (Iran), Poopó (Bolivia), and the Aral Sea itself [5]—and serves as a sobering futures analogue for dryland water bodies currently under combined climatic and hydrological stress in the region (Sarez, Sariqamish, Tudakul).

5.4. Limitations and Future Directions

Several limitations warrant acknowledgement. First, the SEM analysis treats anthropogenic pressure as a time-invariant variable per site, measured at the midpoint of the study period; future work should incorporate annual livestock census data to capture the temporal co-variation between climate and stocking density. Second, the Hamoun site straddles an international boundary, limiting access to concurrent field validation data from the Afghan portion; our accuracy assessment for this site relies exclusively on Iranian-side validation points and likely underestimates classification uncertainty in the eastern playa. Third, the empirical regression-based projection approach does not capture potential threshold or tipping-point behaviour in vegetation response; dynamic vegetation models such as JSBACH or aDGVM2 could be integrated with CMIP6 forcing to address this limitation. Finally, the 30 m Landsat resolution is insufficient to resolve fine-scale heterogeneity within the BSI severe class, which likely comprises a mosaic of completely bare and partially crusted surfaces; Sentinel-2 (10 m) and WorldView-3 (0.3 m) data offer paths to higher-resolution characterisation in priority intervention zones.

6. Conclusions

This multi-site, multi-index, spatio-temporal analysis of desertification dynamics in Central Asian arid zones yields five principal conclusions with direct policy relevance:

1. Regional warming is occurring at 1.4–2.3× the global mean rate (+0.028 to +0.059 °C yr^{-1}), with Hamoun showing the steepest trajectory. Simultaneous precipitation decline at three of four sites is compressing the moisture balance and accelerating the transition towards hyper-aridity across the study domain.
2. Multi-index remote sensing analysis (NDVI, SAVI, BSI, LST, FVC) reveals pervasive and statistically significant degradation across all study sites over 1985–2024, with NDVI losses of 18–34% and BSI increases of 43–112%. Single-index assessments would substantially under-characterise the magnitude and dimensionality of ongoing degradation.
3. SEM identifies both climatic (42–58%) and anthropogenic (38–52%) drivers as major, co-equal contributors to degradation status, with a significant positive covariance indicating non-linear amplification when drought and overgrazing co-

occur. Policy interventions targeting only one driver in isolation will be structurally insufficient.

4. Hotspot mapping identifies pastoral water points, irrigation canal corridors, and abandoned agricultural infrastructure as primary spatial organising principles of severe desertification—actionable targets for site-specific restoration investment.
5. Future projections (SSP2-4.5 and SSP5-8.5) indicate that 61–78% of currently mild desertification zones will transition to moderate or severe status by 2060, underscoring the urgency of scaling up Land Degradation Neutrality interventions—regulated destocking, phytomelioration, and water harvesting—within this decade.

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