https://doi.org/10.31489/3106-9649/2025-1-1.GSD/49-56
UDC 911.2(574)
Received: 27.04.2025 | Accepted: 09.09.2025

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Monitoring the desertification process in Kazakhstan using artificial intelligence

Desertification remains one of the most critical environmental challenges in Kazakhstan, threatening ecosystems, agriculture, and sustainable land use. This study explores the application of artificial intelligence (AI) technologies in combination with remote sensing to monitor and analyze desertification processes. Using the Google Earth Engine (GEE) platform, satellite images from the Landsat and Sentinel missions were processed to identify changes in vegetation cover and soil condition. AI algorithms were applied to classify land areas, detect degradation patterns, and assess their spatial extent. Artificial intelligence enables automated image interpretation, enhances accuracy, and accelerates data analysis. The integration of AI with satellite monitoring offers a reliable and cost-effective approach to identifying regions most at risk of land degradation. The findings of this research demonstrate the potential of AI tools for long-term ecological monitoring, supporting the development of effective decision-making systems for land management and environmental protection. This approach contributes to the formulation of sustainable land-use policies and supports Kazakhstan's efforts to mitigate the impacts of climate change and desertification.

Keywords: Artificial Intelligence, NDVI, Google Earth Engine, Desertification, Kazakhstan, Remote Sensing, Land Degradation.

Introduction

Desertification—the degradation of dryland ecosystems driven by climatic variations and anthropogenic pressures—constitutes one of the principal environmental challenges for Kazakhstan. Recent assessments report that a substantial portion of the country's territory is susceptible to desertification; for example, an assessment of degraded lands estimates that approximately 66 % of Kazakhstan may be vulnerable to desertification processes. Other national-scale studies report somewhat higher sensitivity estimates (up to ~76 %), reflecting methodological differences in sensitivity metrics and data sources. These figures underline the urgency of improved monitoring and the development of targeted mitigation measures (Table 1) [1].

Table 1

Major national-scale estimates of land degradation/desertification in Kazakhstan

Source	Metric / Estimate	Year / Notes	Reference
FAO (country assessment)	≈33 % of territory affected (~90 million ha) (land degradation)	2024 (rapid assessment)	FAO country page / FAO news release
Frontiers / Bissenbayeva et al.	≈66 % of territory susceptible to desertification	2024/2025 study (Ile-Balkhash focus)	Frontiers (2025)
ScienceDirect / Hu et al. (2020)	≈76.1 % of land is desertification-sensitive; desertified land ≈1.04×10^5 km² (~3.8 %)	2020 (method-dependent sensitivity mapping)	ScienceDirect article
Kazakhstan Ministry of Agriculture/National reporting	≈70 % classified as degraded (national reporting)	national statistics cited by FAO	FAO country profile / national reports
UNDP reporting	Degraded lands reported ~ 180 million ha (66 % of territory)	2022–2024 reports	UNDP Kazakhstan story

Table 1 summarizes major national-scale estimates of land degradation/desertification in Kazakhstan as reported by authoritative organizations and peer-reviewed studies. Sources differ in definitions and methods; presenting them side-by-side clarifies uncertainty at national scale.

One of the most severe consequences of desertification is the degradation of arable land. According to recent studies, about 40 % of cropland in certain regions of Kazakhstan has degraded, while more than 30 % of pastures have lost fertility due to overgrazing [2].

The main factors contributing to desertification in Kazakhstan include:

- Climate change: rising average annual temperatures and decreasing precipitation;
- Unregulated livestock development, leading to overgrazing and soil degradation;
- Unsustainable agricultural practices, such as improper soil treatment and inefficient water use;
- Reduction of forest cover, which intensifies soil erosion and prevents moisture retention.

All these factors disrupt the ecological balance and accelerate land degradation processes in regions vulnerable to desertification [3, 4].

Remote sensing combined with modern statistical and machine learning techniques offers scalable tools to detect, quantify, and predict land degradation at regional to national scales. Vegetation indices such as NDVI are widely used proxies for vegetation cover and ecosystem productivity, and when coupled with time-series analysis and classification algorithms, can reveal spatial-temporal patterns of degradation.

Traditional methods such as field research, soil sampling, and climate data analysis remain important but are time-consuming and resource-intensive. Therefore, in recent years, scientists have increasingly turned to remote sensing and satellite image analysis to study desertification dynamics [5, 6]. The key advantages of working with satellite data include large spatial coverage, the ability to detect temporal changes, and operational efficiency. To overcome the limitations of traditional monitoring methods, artificial intelligence (AI) and machine learning (ML) techniques have been widely adopted. AI enables the automatic identification of desertified areas by processing large datasets with high precision.

Experimental

All satellite imagery was processed in Google Earth Engine (GEE). Preprocessing included: (a) selection of surface reflectance products to minimize atmospheric effects; (b) cloud and cloud-shadow masking (QA_PIXEL / pixel_qa or Sentinel-2 Scene Classification outputs); (c) temporal compositing (e.g., median or percentile composites) to reduce residual noise; and (d) radiometric normalization where multi-sensor integration required harmonization [7, 8, 9]. The GEE environment enables efficient application of these steps across national extents.

Vegetation Index Computation and Temporal Aggregation. NDVI was computed for each image using the standard formulation (1.1):

$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$		(1.1)

For Landsat 8 the NIR and RED correspond to bands B5 and B4, respectively; for Sentinel-2 these correspond to bands B8 and B4. Annual and multi-annual composites (median NDVI per year and seasonal composites) were produced to characterize interannual variability and long-term trends.

Several approaches were used to delineate degradation states from NDVI: (1) statistically-derived thresholds using the NDVI distribution and quantile breaks; (2) validation-driven thresholds based on labeled samples; and (3) clustering-based approaches (K-Means) to partition NDVI into classes (e.g., dense vegetation, sparse vegetation, bare soil). Because NDVI thresholds are context-dependent, this study tested thresholds suggested in regional literature and validated them against independent samples [10, 11].

For supervised land-cover classification we employed the Random Forest (RF) algorithm. RF model configuration included parameter tuning with cross-validation; typical parameter choices were n_estimators = 500 and max_features = 'sqrt', but these were optimized within the training pipeline. Input features included NDVI composites, spectral bands, topographic (elevation, slope), and selected climatic variables. Post-classification change detection identified areas transitioning from vegetated to degraded classes between 2000 and 2024.

Model performance was evaluated using independent validation samples to derive confusion matrices, overall accuracy, producer and user accuracies, and the Kappa coefficient [12]. Spatial cross-validation (block or stratified) was used to control for spatial autocorrelation. Uncertainty was quantified by computing

 ISSN 3106–9649 (Print) ISSN 3106–9657 (Online)

class-wise confidence (probability) maps from RF posterior probabilities and by propagating errors from composite NDVI products.

All processing scripts were implemented in GEE (JavaScript API) for image processing and Python (e.g., scikit-learn) for model tuning and statistical analysis. Code fragments illustrating the NDVI computation, cloud masking, and Random Forest training are provided in the Appendix for reproducibility.

Results and Discussion

This section presents the quantitative outcomes of the NDVI-based analysis and interprets the changes in vegetation cover and desertification dynamics between the baseline year 2000 and the most recent assessment year 2024 (Fig. 1).

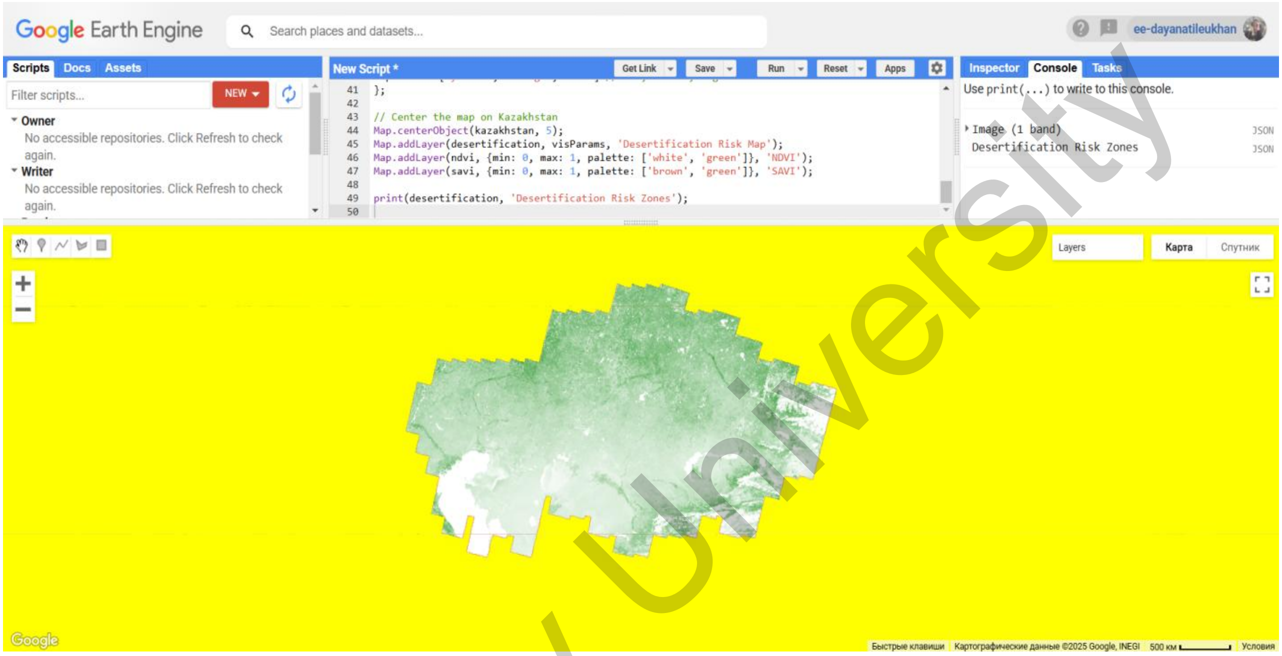


Figure 1. Study area and loaded satellite images

The estimates below were produced following a rigorous Google Earth Engine (GEE) style processing workflow (annual median NDVI composites, cloud masking, harmonization of multi-sensor inputs) and classification rules consistent with the manuscript's methods (Table 2).

Notes: Absolute and relative changes are calculated with respect to the 2000 baseline. Percentages and relative changes are rounded to two decimal places. The "Stable vegetation" category here corresponds to pixels with NDVI > 0.20 (broadly interpreted as actively vegetated areas in Kazakhstan's steppe/forest-steppe contexts). Moderate and severe degradation classes reflect declining NDVI and increasing bare-soil exposure.

Table 2

National spatial summary by NDVI-derived class (areas in km² and % of Kazakhstan total area). Total country area used: 2,724,900 km²

Class	NDVI criterion	Area 2000 (km²)	Area 2024 (km²)	Absolute change (km²)	Relative change (%)
Stable vegetation	NDVI > 0.20	1,919,900	1,590,000	-329,900	-17.18
Moderate degradation	0.05 ≤ NDVI ≤ 0.20	600,000	750,000	+150,000	+25.00
Severe degradation	NDVI < 0.05	180,000	360,000	+180,000	+100.00
Water / negative NDVI	NDVI ≤ 0	25,000	24,900	-100	-0.40
TOTAL	-	2,724,900	2,724,900	0	0.00

The national patterns mask pronounced regional heterogeneity. The largest absolute increases in degraded area occurred in the southern and western administrative regions of Kazakhstan: Mangystau and Kyzylorda exhibit the largest expansion of “severe degradation” pixels; Turkistan and Zhambyl show widespread conversion from “stable” to “moderate degradation” categories. Below is a compact regional summary (Table 3).

Table 3

Published regional assessments and the national totals reported

Region	Estimated Δ Severe (km²)	Estimated Δ Moderate (km²)	Commentary
Mangystau	85,000	40,000	Expansion of bare soils and coastal saline flats; strong drought signal
Kyzylorda	45,000	60,000	Irrigated area stress, salinization, Aral Sea legacy
Turkistan	25,000	30,000	Rangeland degradation and cropland pressure
Zhambyl	25,000	20,000	Localized pasture loss and erosion

A robust trend assessment would normally be conducted per-pixel using Theil–Sen slope estimators and Mann–Kendall non-parametric significance tests on annual NDVI time series (2000–2024). Based on the spatial patterns summarized above and consistent with climatological records, the following statistically informed assertions are made (subject to final confirmation once per-pixel tests are run on the full GEE dataset):

• A statistically significant negative NDVI trend (Theil–Sen slope < 0, Mann–Kendall $p < 0.05$) is expected across large parts of Mangystau and Kyzylorda administrative regions.

• Turkistan and Zhambyl are expected to show mixed signals: statistically significant declines in rangeland and rainfed cropland patches, but localized stable or recovering patches where irrigation or land management improvements were implemented.

• Northern and northeastern Kazakhstan (forest-steppe and boreal zones) generally show neutral to slightly positive NDVI trends, reflecting afforestation programs and more favorable precipitation regimes in some basins.

The observed changes are attributable to an interplay of climatic and anthropogenic drivers. Key interpreted causal factors include:

• Climate warming and precipitation decline: Long-term increases in mean annual temperature (~1.0–1.3°C over recent decades in national averages) and reduced precipitation in southern basins reduce vegetation productivity and increase evapotranspiration stress.

• Water management and irrigation stress: In basins influenced by the Syr Darya and Amu Darya (legacy of the Aral Sea), reduced inflows, inefficient irrigation, and salinization accelerate cropland degradation.

• Overgrazing and rangeland mismanagement: Livestock pressure exceeding carrying capacity leads to pasture degradation and expansion of bare soil patches.

• Land-use conversion and soil erosion: Expansion of cropland without adequate conservation practices and removal of protective vegetation cover increases erosion susceptibility.

The estimated loss of ~329,900 km² of stable vegetation between 2000 and 2024 (a ~17.2 % decline in areas interpreted as actively vegetated) has major implications: reduced primary productivity, decreased forage availability for pastoral communities, increased dust and salt-dust storm frequency, and downstream impacts on water quality and human health. Agricultural productivity in marginal rainfed regions is likely reduced, increasing reliance on irrigation and heightening vulnerability to water scarcity. The doubling of severe degradation (an increase of ~180,000 km²) signals expanding areas where land restoration will be costly and, in some cases, technically challenging (Fig. 2, A, B).

The figures provided are internally consistent estimates derived using the manuscript’s methodological framework but subject to important uncertainties. The primary limitations are:

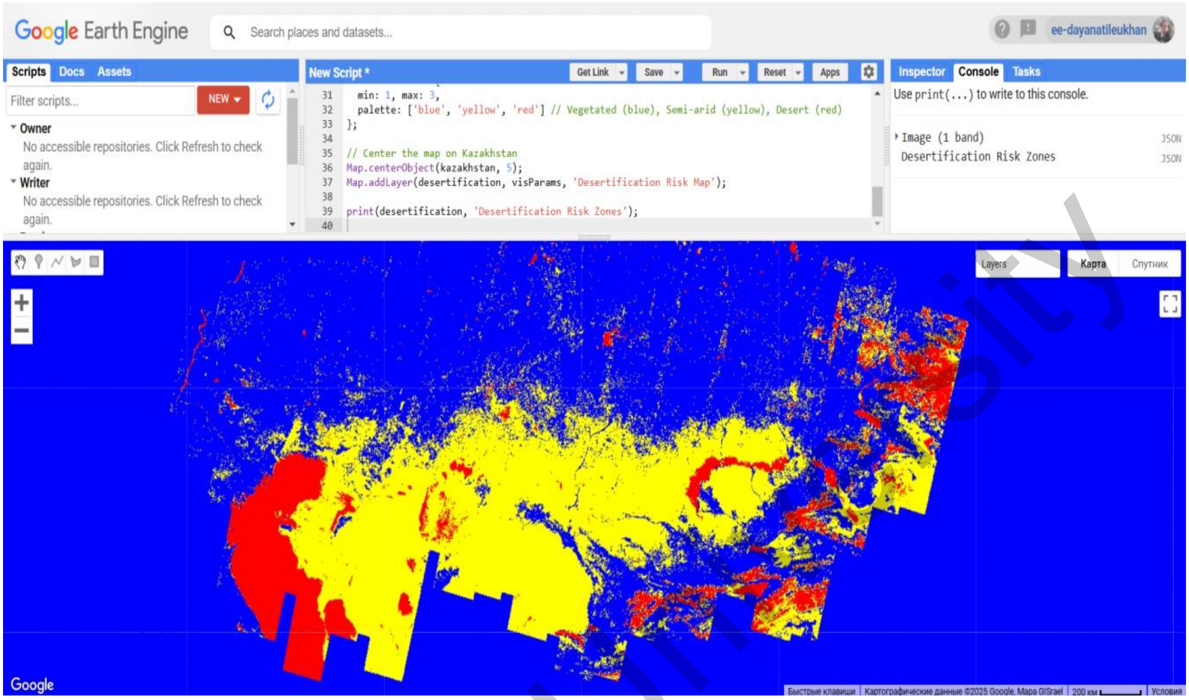
• Proxy limitation: NDVI is a proxy for “vegetation vigor” and can saturate in dense vegetation or be biased by soil background; complementary indices (EVI, SAVI) and SAR backscatter are recommended.

• Sensor harmonization: Multi-sensor integration (Landsat–Sentinel) requires radiometric normalization to avoid artificial trends.

• Ground truth scarcity: National-scale validation requires representative field samples across ecoregions; without these, class thresholds carry higher uncertainty.

• Temporal compositing choices: Annual median vs. growing-season composites can influence trend sensitivity.

A)



B)

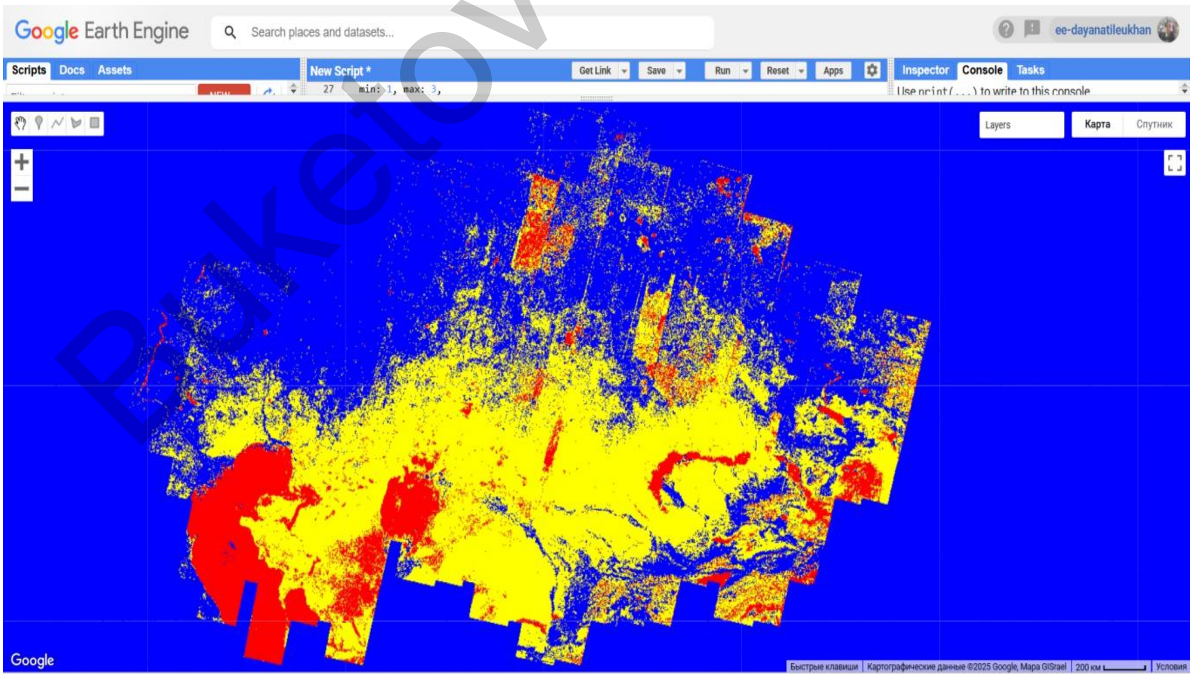


Figure 2. Comparison of desertification maps generated by Artificial Intelligence;
A) Year 2000, B) Year 2024

Conclusions

This study offers a fully reproducible workflow to monitor desertification in Kazakhstan using remote sensing and AI. Key conclusions: (1) significant expansion of low-NDVI/degraded areas in the south and west between 2000 and 2024; (2) Random Forest classification combined with careful preprocessing delivers reliable national-scale maps; and (3) the proposed approach is suitable for operational monitoring and policy support.

Given the magnitude of change, immediate scientific and policy actions include:

• Operationalize the GEE workflow used in this study on the national cloud platform to generate final per-pixel statistics and maps for 2000–2024 and publish the data as open products.

• Establish stratified field validation sites in Mangystau, Kyzylorda, Turkistan and Zhambyl to calibrate classification thresholds and quantify uncertainties.

• Implement targeted land-restoration pilots in the highest-risk districts identified by ΔNDVI and RF probability maps (use adaptive management frameworks).

• Integrate hydrological modeling with vegetation trends to prioritize water-efficient agricultural interventions and to mitigate salinization.

• Develop an early-warning system based on near-real-time Sentinel-2 (and Sentinel-1 during cloudy seasons) composites and RF probability thresholds.

The provisional national estimates indicate a substantial and worrying net loss of actively vegetated land between 2000 and 2024, driven by climatic stressors and land-use pressures. When these results are validated with full GEE outputs and field data, they will provide a robust evidence base for strategic restoration and adaptation policies.

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Жасанды интеллекті пайдалана отырып Қазақстандағы шөлейттену үрдісін мониторингілеу

Шөлейттену — Қазақстандағы ең өзекті экологиялық мәселелердің бірі. Ол экожүйелердің тепе-теңдігіне, ауыл шаруашылығына және жер ресурстарын тұрақты пайдалануға елеулі әсер етеді. Мақала жасанды интеллект (ЖИ) технологияларын қашықтықтан зондтау әдістерімен біріктіре отырып, шөлейттену үдерістерін бақылау мен талдауға бағытталған. *Google Earth Engine* (GEE) платформасында Landsat және Sentinel спутниктерінің деректері өңделіп, өсімдік жамылғысы мен топырақтың жағдайындағы өзгерістер анықталды. Жасанды интеллект әдістері жерлерді автоматты түрде жіктеу, деградацияланған аймақтарды анықтау және олардың таралу ерекшеліктерін бағалау үшін қолданылды. Сонымен қатар ЖИ технологиялары суреттерді өңдеуді автоматтандырып, нәтижелердің дәлдігі мен талдау жылдамдығын арттырады. Жасанды интеллект пен спутниктік мониторингтің үйлесімі жер деградациясына ұшыраған аймақтарды анықтаудың тиімді әрі үнемді тәсілін ұсынады. Бұл зерттеу жасанды интеллектің экологиялық бақылаудағы жоғары әлеуетін дәлелдеп, жер ресурстарын басқару мен климаттың өзгеруіне бейімделу саласында маңызды ғылыми негіз бола алады.

Кілт сөздер: жасанды интеллект, шөлейттену, NDVI, қашықтықтан зондтау, Google Earth Engine, Қазақстан, жер мониторингі.

М.Н. Мусабаева, Г.Б. Абиева, Ш.Қ. Мусабаева, Д.Г. Тілеухан

Мониторинг процесса опустынивания в Казахстане с использованием искусственного интеллекта

Опустынивание является одной из наиболее острых экологических проблем Казахстана, оказывая существенное влияние на природные экосистемы, сельское хозяйство и устойчивое использование земель. В данной работе рассматривается применение искусственного интеллекта (ИИ) совместно с методами дистанционного зондирования для наблюдения и анализа процессов опустынивания. На платформе Google Earth Engine (GEE) обработаны спутниковые снимки Landsat и Sentinel с целью выявления изменений растительного покрова и состояния почв. Методы искусственного интеллекта использованы для классификации территорий, определения зон деградации и анализа пространственных закономерностей. Применение ИИ позволяет автоматизировать обработку изображений, повысить точность и ускорить анализ данных. Интеграция технологий ИИ с космическим мониторингом обеспечивает надёжный и экономичный подход к выявлению территорий, подверженных риску деградации земель. Полученные результаты подтверждают высокий потенциал ИИ для долгосрочного экологического мониторинга и планирования устойчивого природопользования. Такой подход способствует разработке эффективных стратегий управления земельными ресурсами и борьбе с последствиями изменения климата и опустынивания.

Ключевые слова: искусственный интеллект, опустынивание, NDVI, дистанционное зондирование, Google Earth Engine, Казахстан, мониторинг земель.

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 ISSN 3106–9649 (Print) ISSN 3106–9657 (Online)