

Article

An Integrated Earth Observation Assessment of Land-Cover Change, Settlement Expansion, and Tropospheric NO₂ in East Kazakhstan

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Abstract

The East Kazakhstan Region is characterized by heterogeneous mountain, steppe, agricultural, and urban–industrial landscapes. However, spatially integrated assessments of land-cover conditions, agricultural dynamics, settlement expansion, and atmospheric trace-gas patterns remain limited. This study combines open multi-source Earth observation datasets and products to assess regional land cover, cropland dynamics from 2003 to 2019, built-up-area expansion from 1985 to 2025, and tropospheric nitrogen dioxide (NO₂) column density from 2019 to 2024. The land-cover classification was based on Sentinel-2 imagery and ancillary geospatial datasets. Its random forest component achieved an overall accuracy of 90.17%, a Cohen’s kappa coefficient of 0.892, and a macro-averaged F1 score of 0.888. Grassland was the largest mapped land-cover class, covering 39.3% of the study region, followed by dense vegetation (16.2%), rock (14.9%), and sparse vegetation (10.6%). Mapped cropland extent increased from 4771.6 km² in 2003 to 5043.9 km² in 2019, representing a net increase of 272.3 km² (5.7%), although a minor decrease occurred after 2015. The harmonized built-up area time series showed expansion within all nine major settlements, with the largest absolute increase observed in Öskemen (Ust-Kamenogorsk). Newly detected built-up pixels during 2000–2024 were mostly associated with transition from grassland and dense shrubs. Annual Sentinel-5P observations showed recurring elevated tropospheric NO₂ column densities in northwestern East Kazakhstan, particularly around Öskemen. Over the built-up footprint, the area-weighted mean increased from 24.1 μmol m^{−2} in 2019 to 29.2 μmol m^{−2} in 2024. The integrated framework provides a spatially consistent regional baseline while identifying descriptive patterns that require further process-based investigation in future.

Keywords: East Kazakhstan; land use and land cover (LULC); built-up expansion; cropland dynamics; nitrogen dioxide (NO₂)



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1. Introduction

Urbanization and agricultural intensification are among the dominant drivers of environmental change worldwide. The expansion of settlements, infrastructure, and agricultural

production systems has substantially altered natural landscapes, affecting ecosystem functioning, hydrological processes, biodiversity, and atmospheric conditions [1,2]. Consequently, understanding spatial and temporal patterns of land transformation has become an important component of environmental monitoring and sustainable land management.

Land-use and land-cover (LULC) change represents one of the most direct indicators of anthropogenic influence on terrestrial ecosystems. The conversion of natural vegetation, grasslands, wetlands, and agricultural land into built-up areas can lead to habitat fragmentation, biodiversity loss, soil degradation, and modifications of ecosystem services [3–5]. Quantifying these transformations is essential for assessing the long-term environmental impact on ecology and supporting evidence-based land management and planning decisions. Recent advances in Earth observation (EO) technologies have significantly improved the capability to monitor land-cover dynamics across large spatial extents and long temporal periods, providing consistent and repeatable information on environmental change [6,7].

In this context, Central Asia represents an important region for investigating the interactions between urban development, agricultural transformation, and environmental change. Following the breakdown of the Soviet Union, the region experienced profound socio-economic restructuring that affected agricultural production systems, industrial activities, settlement development, and land management practices [8–10]. The Republic of Kazakhstan, the largest country in Central Asia, is characterized by extensive steppe ecosystems, desert and semi-deserts and mountain environments. During recent decades, economic development has been strongly influenced by mining, metallurgy, energy production, and agricultural modernization, resulting in substantial changes in land-use patterns and increasing environmental pressures [11]. Satellite-based analyses have documented considerable changes in cropland extent, grassland conditions, and settlement development throughout Kazakhstan and neighboring regions [12–14]. Furthermore, recent assessments suggest that land-cover transitions across Central Asia are increasingly linked to vegetation degradation, ecosystem stress, and broader climate-related impacts [12].

The East Kazakhstan Region (EKR) represents one of the most environmentally and economically important regions of Kazakhstan. Located within the transition zone between the Kazakh Steppe and the Altai Mountain system, the region encompasses highly diverse landscapes including forests, grasslands, agricultural areas, wetlands, and alpine ecosystems. At the same time, East Kazakhstan hosts several major industrial centers such as Ust-Kamenogorsk (Öskemen), Ridder, and Altai, which are closely associated with mining and non-ferrous metallurgy. These industries constitute important economic drivers but also represent significant sources of environmental pollution and ecosystem pressure [15,16]. Consequently, East Kazakhstan provides a suitable case study for investigating the relationships between land transformation, urban development, and environmental conditions.

Satellite-based EO offers unique opportunities to analyze these processes in a spatially consistent framework. Sentinel-2 satellites provide high spatial resolution multispectral observations suitable for detailed land-cover characterization and monitoring [17]. In addition, recent global geospatial settlement products such as the World Settlement Footprint (WSF) provide opportunities for quantifying urban growth and settlement dynamics at regional and global scales [18,19]. Complementary well established global datasets such as ESA WorldCover and the JRC Global Surface Water product further support consistent land-cover assessments across large regions [20,21]. Beyond land-cover dynamics, atmospheric pollution has become an increasingly important indicator of environmental quality and anthropogenic pressure. Nitrogen dioxide (NO₂) is closely linked to industrial activities, fossil fuel combustion, power generation, transportation, and residential heating and is therefore frequently used as an indicator of urban and industrial emissions [22].

The Sentinel-5 Precursor mission has significantly enhanced global monitoring capabilities for atmospheric trace gases by providing continuous observations with high temporal frequency and near-global coverage [23]. In East Kazakhstan, elevated NO₂ concentrations have repeatedly been associated with emissions from metallurgical complexes, mining operations, coal-fired power generation, and urban combustion sources [15]. These pollution patterns are further influenced by complex mountain–valley circulation systems that can enhance pollutant accumulation and reduce atmospheric dispersion [24].

Despite the environmental and economic importance of East Kazakhstan, previous studies have predominantly focused on individual aspects such as industrial pollution, agricultural change, or regional land-use dynamics. Integrated assessments that simultaneously investigate land-cover conditions, urban expansion, agricultural development, and atmospheric pollution remain limited. Such analyses are particularly relevant in East Kazakhstan, where industrial production, settlement growth, and agricultural activities interact within a highly heterogeneous environment.

This study addresses this gap by integrating multiple EO datasets to assess land-cover conditions, cropland dynamics, urban expansion, and atmospheric pollution patterns across East Kazakhstan. Specifically, the objectives are to (1) map and quantify the current land-cover composition and cropland development of the region using multi-source EO and geospatial datasets, (2) assess the spatial and temporal patterns of urban expansion using World Settlement Footprint products, and (3) evaluate recent NO₂ patterns in relation to urban and industrial areas using Sentinel-5P products. By combining complementary datasets within a consistent geospatial framework, the study provides a comprehensive assessment of environmental conditions in East Kazakhstan and contributes to a better understanding of the interactions between urbanization, land transformation, and atmospheric pollution.

2. Study Region

The study focuses on the East Kazakhstan Region (EKR), located in eastern Kazakhstan (Figure 1). Following the administrative reorganization in 2022, the region now covers approximately 97,700 km² and has its administrative and industrial center in Öskemen (Ust-Kamenogorsk). The region borders Abai Region to the west, the Russian Federation to the north and northeast, and China to the south and southeast and spans the transition from the Kazakh Steppe to the Altai Mountains [25].

The region is characterized by pronounced physiographic heterogeneity, including mountain systems, intermontane basins, river valleys, steppe landscapes, and semi-arid lowlands. The eastern and northeastern parts are dominated by the Kazakh Altai Mountains, which form the southwestern extension of the Greater Altai Mountain system [26]. The elevation ranges from approximately 200 m in the Zaisan Basin to more than 4000 m in the high Altai, creating strong gradients in climate, vegetation, hydrology, and land use (Figure 1). While mountainous environments dominate the eastern and northeastern parts of the region, extensive steppe and semi-arid landscapes characterize the central and southern areas.

The regional drainage network is dominated by the Irtysh River and its tributaries. The tributaries, including the Bukhtarma, Ulba, and Uba rivers, drain large parts of the region and support agricultural production, hydropower generation, industrial activities, and urban water supply. Major water bodies include Lake Zaisan and the Bukhtarma Reservoir. Snow accumulation and subsequent snowmelt in the Altai Mountains contributes to runoff in the Irtysh River system [27,28].

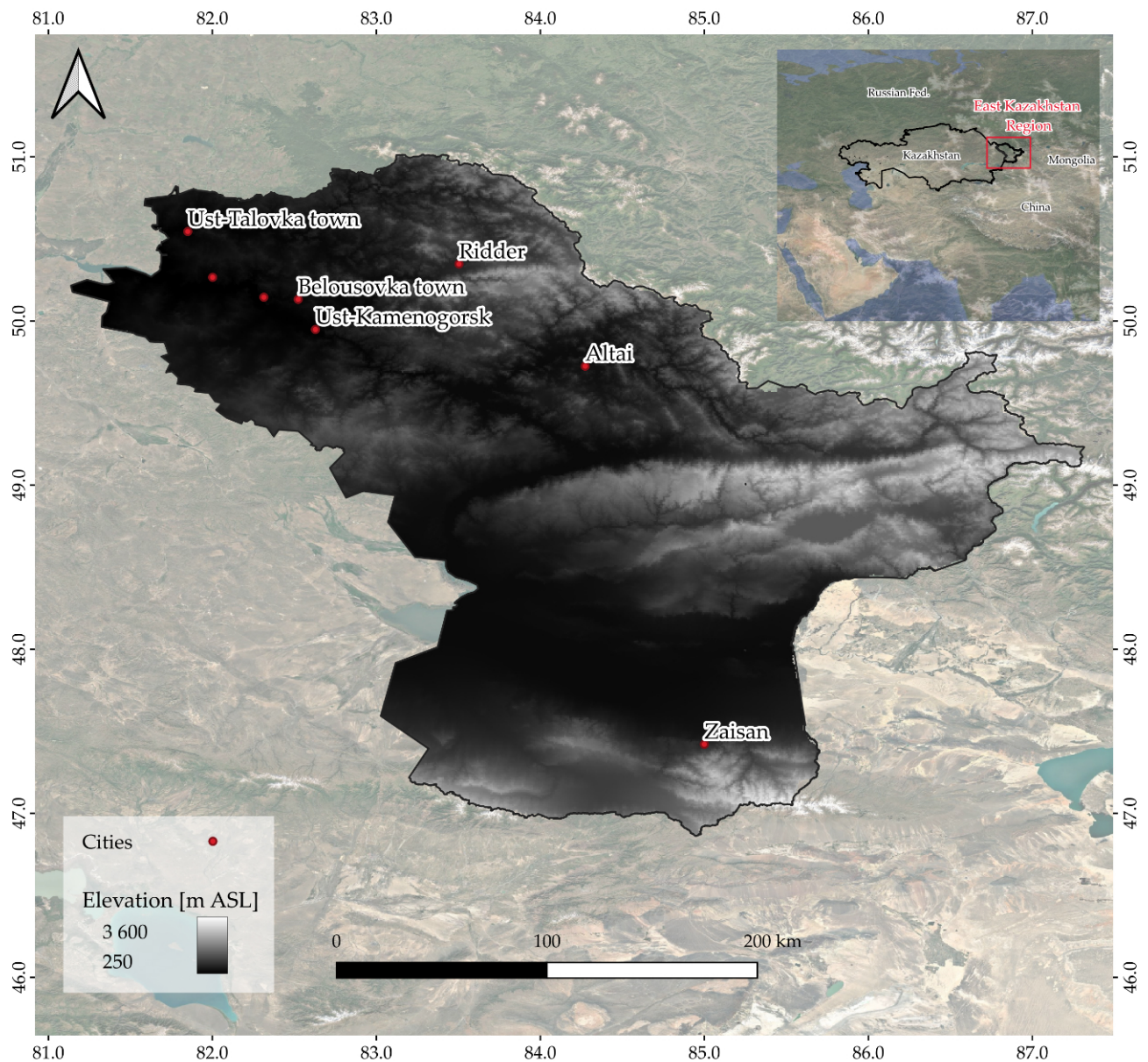


Figure 1. Geographic location and Digital Elevation Model (DEM) of East Kazakhstan Region.

The climate is strongly continental, with cold winters and warm to hot summers. The temperature conditions vary with the elevation and topography. The annual precipitation shows pronounced spatial variability, increasing from less than 300 mm in the semi-arid basin areas to more than 1000 mm in high-elevation part of the Altai Mountains [29]. These climatic gradients result in a mosaic of ecosystems ranging from montane forests and alpine meadows to grasslands, shrublands, croplands, and semi-desert environments.

The regional economy is strongly influenced by mining, metallurgy, energy production, and agriculture. Öskemen (Ust-Kamenogorsk), together with the cities of Ridder and Altai and numerous smaller mining settlements, forms a major regional cluster of mining and non-ferrous metallurgy with large deposits of lead, zinc, copper, gold, silver, and rare metals [30]. In this regard, published studies have documented air quality and associated public-health concerns in industrial centers of East Kazakhstan, particularly Öskemen and Ridder [15,16].

3. Materials and Methods

3.1. Regional Land-Cover Classification

A regionally adapted land-cover classification workflow was developed to characterize the heterogeneous landscapes of East Kazakhstan and to provide a land-cover baseline for this study region. The classification approach was designed to account for the pronounced environmental gradients of the study area. The classification framework integrated multi-temporal Sentinel-2 imagery, derived spectral indices, and ancillary geospatial datasets within a hierarchical classification approach (Figure 2, Supplementary Table S1). Temporally stable land-cover classes were identified first, followed by the differentiation of vegetation, agricultural, and spectrally distinct bare-soil classes.

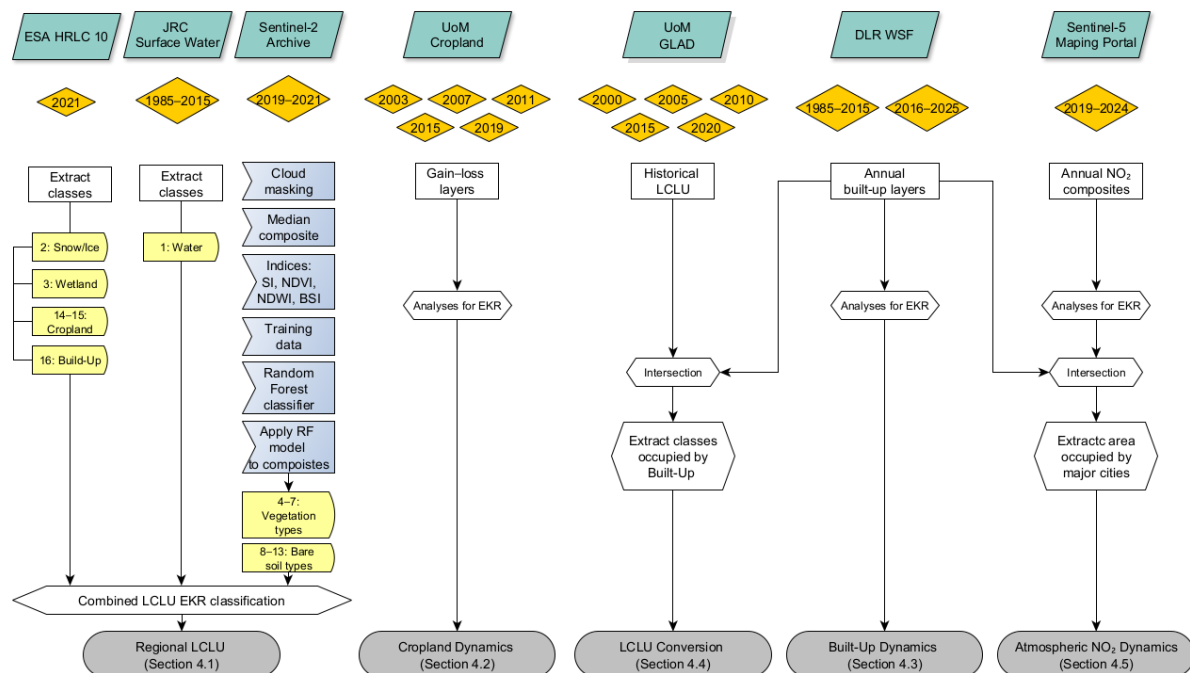


Figure 2. Integrated workflow of the datasets, processing steps, and analyses used to assess land-cover and environmental change in East Kazakhstan Region (EKR).

The primary input data consisted of Sentinel-2 Level-2A surface reflectance imagery acquired through the Copernicus Programme. Sentinel-2 provides multispectral observations with spatial resolutions of 10–20 m and a revisit frequency of approximately five days, making it suitable for regional land-cover mapping and environmental monitoring [17]. To reduce the influence of cloud contamination and short-term seasonal variability, summer median composites were generated using all available Sentinel-2 observations acquired between June and August for the three-year period 2019–2021. Several spectral indices were calculated to improve the class separability and support the identification of specific land-cover characteristics: the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Bare Soil Index (BSI), and the Salinity Index (SI) [31–35].

For representation, 4780 reference samples were derived across Kazakhstan through visual interpretation of Sentinel-2 composites and high-resolution Google Earth satellite imagery. This broader sampling domain was used to represent the environmental and spectral variability of semi-arid, mountainous, agricultural, and bare soil landscapes occurring within East Kazakhstan. The spectral classification was performed using a random forest classifier [36,37], which was subsequently applied to the EKR study area.

The classification procedure followed a hierarchical workflow (Figure 2). To support the classification process and improve the representation of stable land-cover classes,

ancillary geospatial datasets were incorporated. The ESA WorldCover dataset was used as auxiliary information for the identification of permanent snow/ice, wetlands, cropland, and built-up areas [21]. Seasonal and permanent surface water were further refined using the Joint Research Centre (JRC) Global Surface Water dataset, which provides long-term information on water occurrence and seasonality derived from the Landsat archive [20].

The remaining natural landscapes were classified using spectral information derived from Sentinel-2 composites and the associated spectral indices. Particular attention was given to the differentiation of sparsely vegetated and bare-soil environments, which represent extensive landscape components within East Kazakhstan. Due to the pronounced spectral heterogeneity of semi-arid environments, six separate bare-soil classes were introduced to better represent regional surface conditions. The three saline-soil subclasses were subsequently aggregated into one saline-soil class.

3.2. Cropland Development

To investigate agricultural land-use dynamics in East Kazakhstan, the global cropland dataset developed by [38] was used. The dataset provides globally consistent information on cropland extent change for five four-year intervals derived from dense Landsat time series and machine-learning-based classification at a spatial resolution of 30 m. The temporal epochs cover 2000–2003, 2004–2007, 2008–2011, 2012–2015, and 2016–2019.

The original dataset was clipped to the administrative boundaries of EKR. Cropland layers were extracted for the five available observation epochs represented by 2003, 2007, 2011, 2015, and 2019. For the calculation of areas, the clipped raster layers were reprojected to the Equal Earth coordinate reference system (EPSG:6933), which provides an equal-area representation suitable for regional area estimation. Nearest-neighbor resampling was used to preserve the categorical cropland values during reprojection.

Cropland extent was calculated for each available observation epoch using area-based statistics. Net changes in cropland extent were calculated for the consecutive intervals 2003–2007, 2007–2011, 2011–2015, and 2015–2019, as well as for the complete 2003–2019 observation period. In addition to epoch-specific area statistics, a pixel-based change detection analysis was performed to identify stable cropland, cropland gain, and cropland loss between consecutive observation epochs and between 2003 and 2019.

The resulting transition maps enabled the identification of spatial patterns of agricultural expansion and contraction across the study area. Areas classified as cropland in both epochs of a given comparison were considered stable agricultural land, whereas transitions from non-cropland to cropland were classified as cropland gains and transitions from cropland to non-cropland as cropland loss.

3.3. Built-Up Area Expansion Analysis

Long-term built-up area development in East Kazakhstan was assessed using two complementary products of the World Settlement Footprint (WSF) suite including WSF Evolution and WSF Tracker developed by the German Aerospace Center (DLR). WSF Evolution provides annual information on the global settlement extent from 1985 to 2015 at a spatial resolution of 30 m. It was generated from Landsat-5/7 observations and assigns each detected settlement pixel an estimated year of first settlement detection between 1985 and 2015 [39]. WSF Tracker complements this historical product by monitoring built-up area change at approximately 10 m spatial resolution and six-month intervals from July 2016 onward. The Tracker is based on observations from the Sentinel-1 and Sentinel-2 missions [40].

For this study, both products were clipped to the administrative boundary of East Kazakhstan and used to reconstruct settlement development between 1985 and 2025. To obtain a common annual temporal resolution, the two half-yearly Tracker observations

associated with each calendar year were combined into a single annual layer. All pixels classified as built-up before or during the respective year were included in the cumulative settlement extent. This approach enabled the reconstruction of both historical settlement and newly detected built-up areas. For area calculation, the annual cumulative built-up layers were reprojected (EPSG:6933), nearest-neighbor resampling was applied to preserve the categorical raster values, and the built-up area was calculated in square kilometers.

To evaluate the spatial differences in settlement dynamics, the built-up area expansion was analyzed separately for the nine largest cities and settlements of East Kazakhstan. Individual masks were defined around Öskemen (Ust-Kamenogorsk), Ridder, Altai, Shemonaikha, Belousovka, Glubokoe, Pervomaisk, Ust-Talovka, and Zaisan.

For each settlement, annual built-up area statistics were derived from the cumulative WSF layers within the corresponding analysis mask. The resulting time series were used to compare patterns of built-up area development among the selected settlements. The combined WSF dataset was subsequently integrated with the regional land-cover classification and historical land-cover datasets to identify land-cover conversion associated with settlement expansion.

3.4. Analysis of Tropospheric NO₂ Using Sentinel-5P Observations

Regional patterns of tropospheric nitrogen dioxide (NO₂) column density were examined using satellite-derived observations obtained from the Sentinel-5 Precursor (Sentinel-5P) mission. Sentinel-5P carries the TROPospheric Monitoring Instrument (TROPOMI), which provides daily global observations of atmospheric trace gases at high temporal frequency [23,41]. NO₂ was selected because its tropospheric column product provides spatially continuous satellite observations that can be compared across East Kazakhstan.

Annual NO₂ composites were obtained from the Sentinel-5P Product Algorithm Laboratory (S5P-PAL) Mapping Portal. The downloaded Level-3 rasters were derived from Collection 3 of the operational Sentinel-5P NO₂ Level-2 product. Annual datasets were acquired for the period 2019–2024. All datasets were clipped to the administrative boundaries of East Kazakhstan and reprojected (EPSG:4326).

The annual composites were used to describe the regional spatial distribution of tropospheric NO₂ column density and its interannual variability. Spatial patterns were examined in relation to the locations of settlements and built-up areas; however, no source-apportionment analysis was performed.

For the built-up area analysis, a settlement footprint was generated from WSF Tracker (Section 3.3). This same spatial footprint was applied to every annual NO₂ composite from 2019 to 2024, ensuring that differences among years were not caused by changes in the spatial extent of the extraction mask. To account for the difference in spatial resolution between WSF and S5P-PAL, each original NO₂ grid cell was weighted according to the surface area of WSF-derived built-up pixels located within that cell. Annual area-weighted means, medians, standard deviations, and distributional percentiles were subsequently calculated. Thus, the resulting statistics describe the annual differences in satellite-observed tropospheric NO₂ column density over the defined built-up footprint.

3.5. Geospatial Processing and Statistical Summaries

To quantify environmental change, a series of geospatial and statistical analyses were performed. The analytical workflow included categorical raster processing, spatial clipping, reprojection, area calculation, pixel-based change detection, spatial overlay, and descriptive statistical summaries.

The analysis consisted of four major components: (i) land-cover composition assessment; (ii) cropland change analysis; (iii) built-up area expansion assessment; and (iv) tropospheric

NO₂ assessment. Categorical land-cover, cropland, and built-up area rasters were processed using nearest-neighbor resampling to preserve their original class values. Area statistics were calculated in square kilometers using the equal-area coordinate reference system EPSG:6933. The integrated workflow was used to compare the spatial and temporal patterns represented by the individual datasets. No multivariate regression, formal source-attribution model, or causal coupling analysis was performed. Accordingly, spatial concurrence or parallel temporal changes among land cover, settlement extent, cropland, and NO₂ were interpreted as descriptive associations rather than evidence of causal relationships.

4. Results

4.1. Land-Cover Classification of East Kazakhstan Region

The land-cover classification derived from multi-source EO and ancillary geospatial datasets revealed a heterogeneous landscape structure across East Kazakhstan (Figure 3). The random forest component of the classification workflow was evaluated using a stratified 80:20 split of the available reference samples into training and hold-out validation subsets. Samples assigned to the validation subset ($n = 956$) were not used for model fitting. The validation produced an overall accuracy of 90.17%, a Cohen's kappa coefficient of 0.892, and a macro-averaged F1 score of 0.888 (Supplementary Figure S1, after [42]).

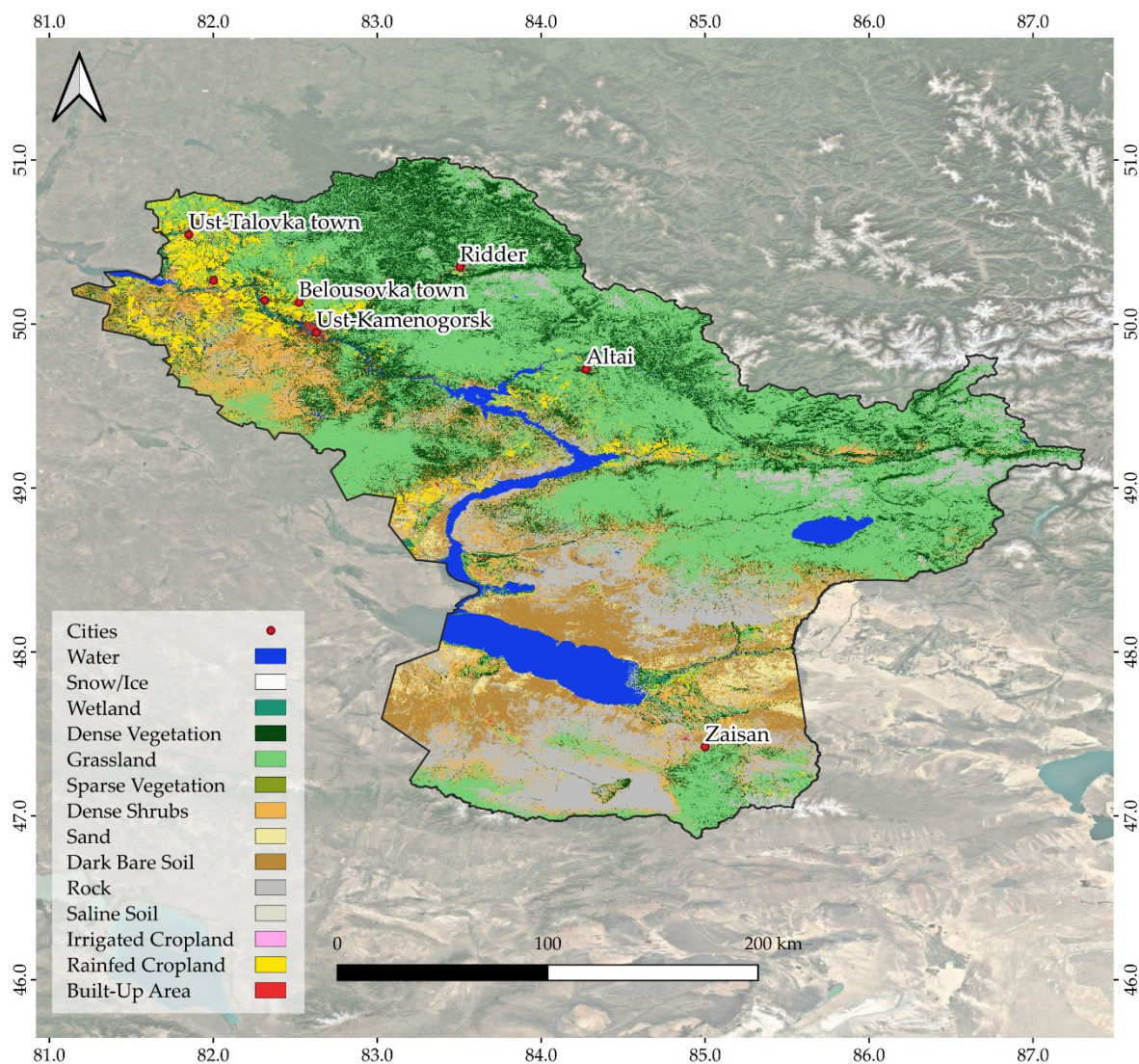


Figure 3. Sentinel-2-based land-cover classification of East Kazakhstan Region.

The resulting land-cover map shows the pronounced spatial heterogeneity of the region, ranging from densely vegetated mountain areas in the Altai Mountains to extensive grasslands, sparsely vegetated and bare surfaces, agricultural areas, and built-up areas. The spatial distribution of land-cover classes exhibited clear geographic patterns. Dense vegetation was concentrated primarily in the mountainous northeastern and eastern parts of the region, particularly within the Altai Mountains. In contrast, grasslands were widely distributed across the central and southern parts of East Kazakhstan. Sparse vegetation, bare-soil, and rock surfaces occurred mainly in the southern and southwestern parts of the region, including areas surrounding the Zaisan Basin. Water bodies were primarily associated with the Irtysh River system, Lake Zaisan, and the Bukhtarma Reservoir. Agricultural land was concentrated primarily in the northwestern part of the region and in lowland and valley areas. Rainfed cropland represented the dominant agricultural type, while irrigated cropland occurred locally. Built-up areas occupied a small proportion of the classified area and were clustered around Öskemen (Ust-Kamenogorsk), Ridder, Altai, Shemonaikha, and several smaller settlements.

Overall, natural and semi-natural land-cover classes dominated the region. Grassland represented the largest land-cover category, accounting for approximately 39% of the total area, followed by dense vegetation (16%), bedrock surfaces (15%), sparse vegetation (11%), and bare-soil (7%) (Figure 4). Water bodies covered approximately 5% and rainfed cropland covered approximately 3.5% of the study area. Snow and ice, wetland, irrigated cropland, and built-up area each accounted for smaller proportions of the classified area.

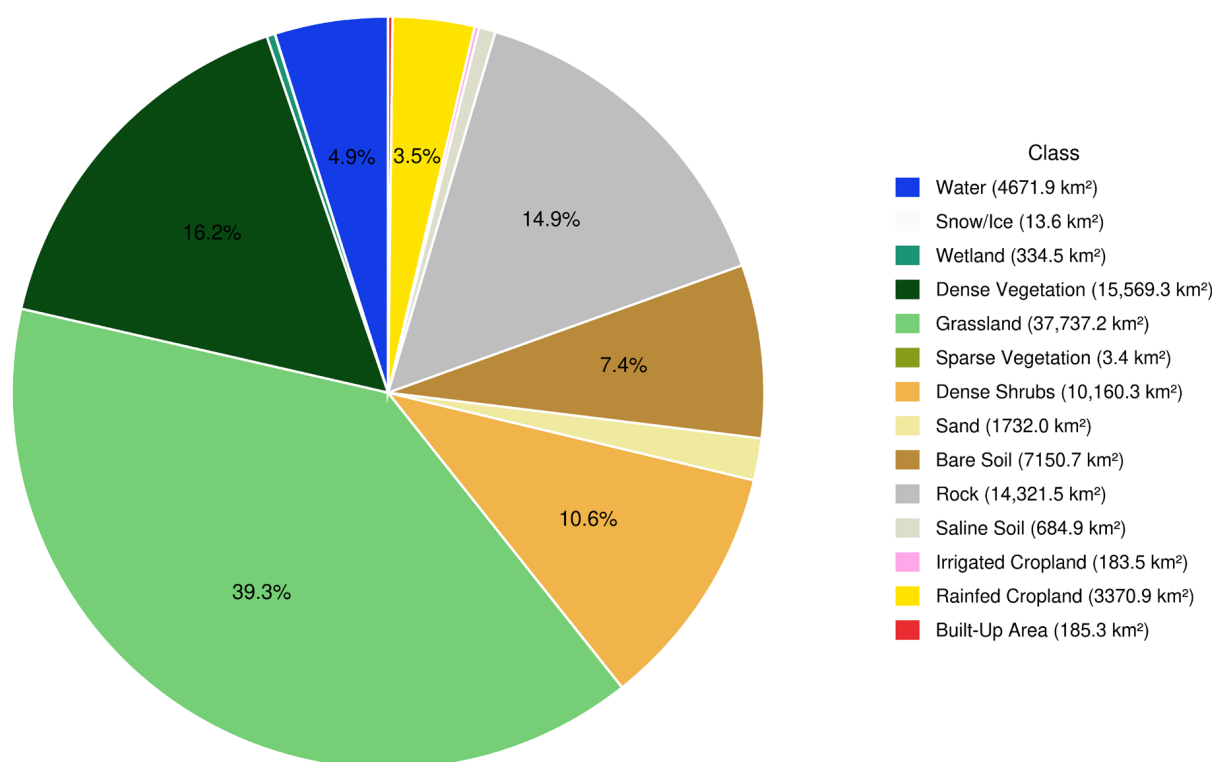


Figure 4. Percentage composition of the land-cover classification within East Kazakhstan Region.

4.2. Cropland Dynamics (2003–2019)

The analysis of the cropland dynamics revealed a net increase in the mapped cropland extent between the epochs represented by 2003 and 2019, although the magnitude and direction of change varied among the four periods. The total cropland extent increased from 4772 km² in 2003 to 5044 km² in 2019, corresponding to an overall increase of approximately 272 km² or 5.7% during the sixteen-year observation period. The temporal evolution

of cropland area was characterized by a gradual small increase between 2003 and 2015, followed by a slight decline after 2015. The mapped cropland extent increased to 4906.5 km² in 2007, 4996.9 km² in 2011, and 5058.9 km² in 2015. The corresponding interval-specific net changes were +134.8 km² between 2003 and 2007, +90.4 km² between 2007 and 2011, and +62.0 km² between 2011 and 2015. Between 2015 and 2019, the mapped cropland extent decreased by 15.0 km².

The spatial distribution of cropland remained highly clustered throughout the study period (Figure 5). Agricultural land was primarily concentrated within the northwestern and western parts of the region, where climatic conditions, topography, and soil properties are favorable for crop production. The spatial patterns show that the cropland gain and loss were concentrated mainly within and around the established agricultural areas in the northwestern and western parts of EKR. Smaller and more spatially isolated changes were mapped in the central and southern parts of the region.

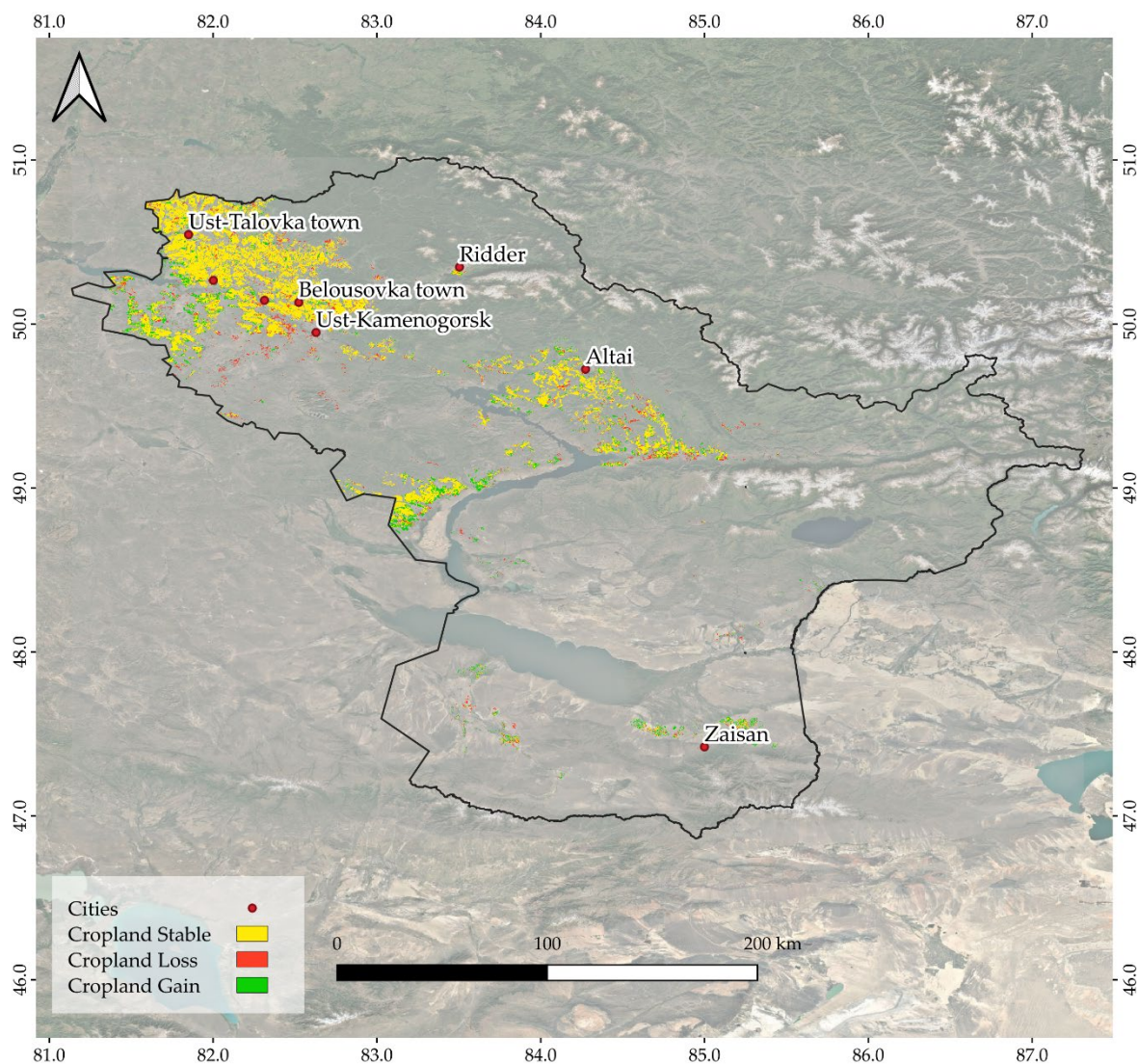


Figure 5. Spatial distribution of cropland persistence, gain, and loss in East Kazakhstan Region between 2003 and 2019.

The cropland transition analysis revealed both cropland persistence and minor bidirectional transitions between the 2003 and 2019 epochs (Figure 5). Across the study area, 4125 km² were classified as cropland in both the 2003 and 2019 layers. Gross cropland gain amounted to 919 km², whereas gross cropland loss amounted to 647 km², resulting in a

net increase of 272 km². Cropland gain areas were primarily located adjacent to existing cropland concentrations and followed recognizable landscape patterns across the north-western and western parts of the region. In contrast, the cropland losses appeared more fragmented and spatially dispersed.

4.3. Built-Up Area Dynamics (1985–2025)

The combined WSF Evolution and WSF Tracker time series showed an increase in detected cumulative built-up area across all nine settlement-specific analysis windows between 1985 and 2025 (Figure 6). Although built-up areas occupy only a relatively small fraction of the regional territory, the observed built-up expansion indicates considerable change over the last four decades.

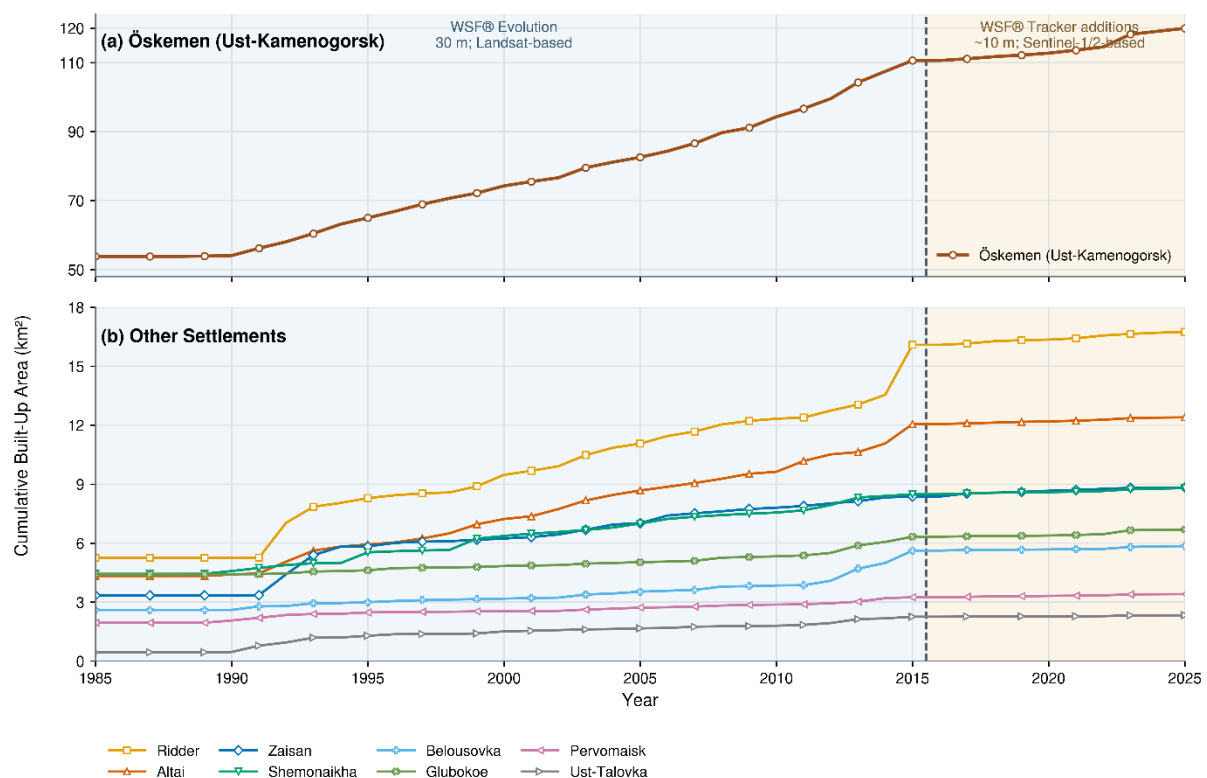


Figure 6. Harmonized cumulative built-up area trajectories within nine settlement-specific analysis windows in East Kazakhstan from 1985 to 2025. (a) Öskemen (Ust-Kamenogorsk); (b) the eight smaller settlements shown using an enlarged y-axis range.

The spatial distribution of detected built-up area was highly uneven and concentrated around a limited number of settlements. The largest absolute increase occurred in Öskemen (Ust-Kamenogorsk), followed by Ridder, Altai, Shemonaikha, Belousovka, Glubokoe, Ust-Talovka, and Pervomaisk.

Öskemen had the largest mapped built-up extent throughout the observation period (Figure 7 and Supplementary Figure S2). The cumulative built-up area increased from approximately 53.8 km² in 1985 to 119.9 km² in 2025, corresponding to an increase of approximately 66.1 km². Of this increase, 56.8 km² were mapped by WSF Evolution between 1985 and 2015, while an additional 9.3 km² were detected by WSF Tracker between the 2016 and 2025. Ridder exhibited the second-largest settlement footprint within the region. Its cumulative built-up area increased from 5.3 km² in 1985 to 16.7 km² in 2025, representing an absolute increase of 11.4 km². Altai also showed an increase in detected cumulative built-up area, from 4 km² in 1985 to 12 km² in 2025. Zaisan increased from 3.3 to 8.8 km², while Shemonaikha increased from 4.4 to 8.8 km². The remaining settlements,

including Belousovka, Glubokoe, Pervomaisk, and Ust-Talovka had smaller cumulative built-up extents in 2025.

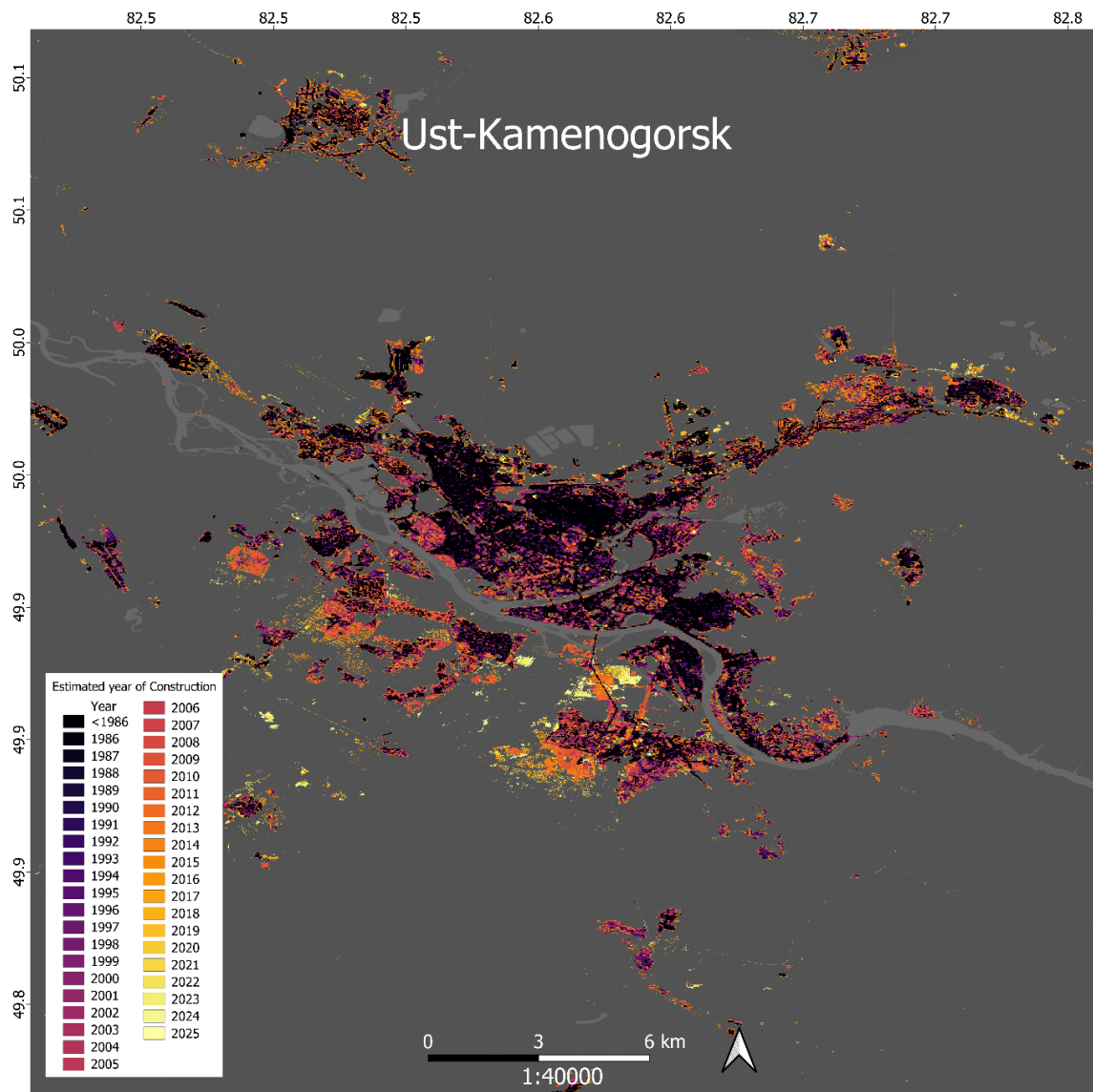


Figure 7. Spatial distribution of estimated settlement-detection periods within the Öskemen (Ust-Kamenogorsk).

Temporal differences in the mapped built-up trajectories were also evident. For Öskemen, the WSF Evolution component increased from 53.8 km² in 1985 to 74.2 km² in 2000 and to 110.6 km² in 2015. Following the transition to WSF Tracker, the harmonized cumulative area increased from the 2015 baseline of 110.6 km² to 119.9 km² in 2025. Similar flattening of the apparent trajectories after 2015 was observed for the other settlements. However, the change in the apparent slope coincides exactly with the transition from the 30 m Landsat-based WSF Evolution product to the 10 m Sentinel-1/2-based WSF Tracker. The pre- and post-2015 slopes therefore cannot be interpreted directly as evidence of a change in the actual rate of settlement development but are an effect of higher spatial resolution and resulting higher detail discrimination of built-up area.

Between 1985 and approximately 2000, built-up expansion occurred relatively slowly across most settlements. A noticeable acceleration of urban development occurred after

approximately 2005. This trend was particularly pronounced in Öskemen, Ridder, and Altai, where built-up areas expanded more rapidly than during previous decades.

Overall, the harmonized WSF record documents increases in detected cumulative built-up area across all nine analysis windows. Öskemen accounted for the largest absolute mapped increase, while the remaining settlements showed substantially smaller changes.

4.4. Land-Cover Conversion Associated with Newly Detected Built-Up Areas

To characterize the land-cover changes [43] associated with built-up area expansion, WSF pixels assigned to five temporally distinct time intervals were intersected with the land-cover layer representing the beginning of the respective period. The analyzed time intervals comprised 2000–2004, 2005–2009, 2010–2014, 2015–2019, and 2020–2024 (Figure 8). Among the five analyzed classes, grassland represented the largest land cover that was reconverted to built-up areas in every period. The area associated with newly detected built-up pixels increased from 1.13 km² in 2000–2004 and 1.23 km² in 2005–2009 to 3.14 km² in 2010–2014, 3.50 km² in 2015–2019, and 4.32 km² in 2020–2024. Dense shrubs represented the second-largest associated class, with values of 0.40, 0.65, 0.53, 2.29, and 0.75 km² across the five successive periods. The corresponding areas of rainfed cropland were substantially smaller, amounting to 0.06 km² in 2000–2004, 0.09 km² in 2005–2009, 0.28 km² in 2010–2014, 0.15 km² in 2015–2019, and 0.57 km² in 2020–2024. Sparse vegetation and dense vegetation generally represented only minor proportions of the analyzed land-cover associations.

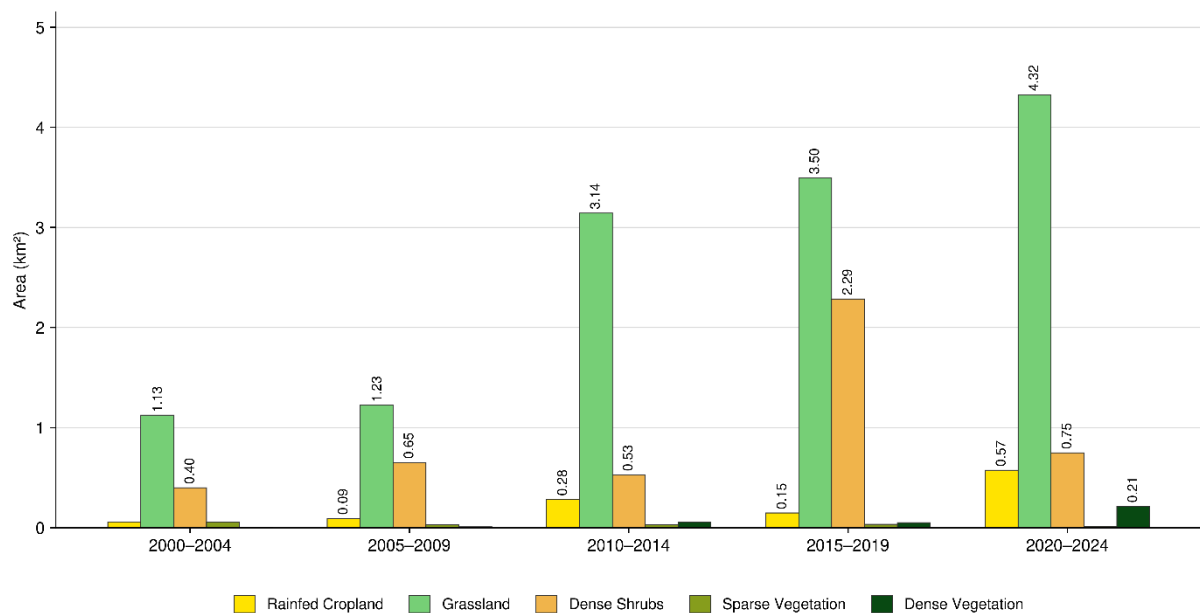


Figure 8. Land-cover conversion associated with built-up area expansion for the periods 2000–2004, 2005–2009, 2010–2014, 2015–2019, and 2020–2024.

Aggregated across all five periods, grassland accounted for 13.31 km² of the analyzed land-cover associations, followed by dense shrubs with 4.61 km² and rainfed cropland with 1.15 km². Dense vegetation and sparse vegetation accounted for 0.33 and 0.16 km², respectively.

4.5. Atmospheric NO₂ Dynamics (2019–2024)

Annual Sentinel-5P observations showed recurring spatial patterns of elevated tropospheric NO₂ column density across East Kazakhstan between 2019 and 2024 (Figure 9, Supplementary Figure S3). In the 2024 composite, the highest tropospheric NO₂ column densities occurred in the northwestern part of the study region, with the most pronounced spatial maximum located around Öskemen (Ust-Kamenogorsk). Elevated values extended

across parts of the northwestern urban–industrial corridor, whereas substantially lower values characterized large parts of the southern study area, including the Zaisan Basin (Figure 9). Similar broad spatial patterns were visible in the annual composites for the preceding years, although the magnitude of the observed NO₂ column densities varied among years.

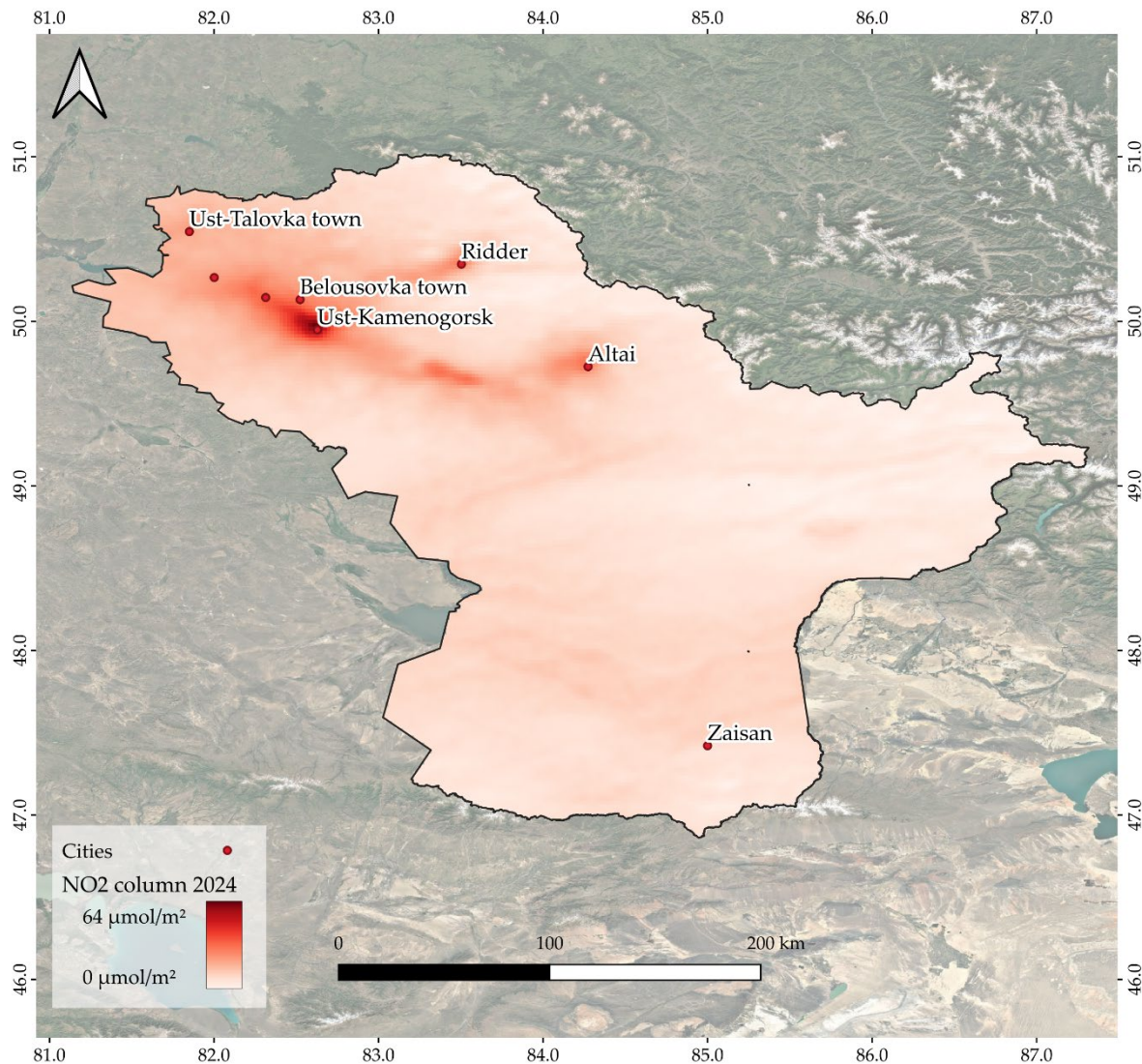


Figure 9. Spatial distribution of annual mean tropospheric NO₂ column density across East Kazakhstan Region in 2024.

The spatial distribution of atmospheric NO₂ remained relatively stable between 2019 and 2024. However, the intensity and spatial extent of elevated concentration zones increased in several industrial and urban areas during the most recent years of observation.

For the quantitative temporal comparison, annual tropospheric NO₂ column densities were evaluated over a static WSF-derived built-up footprint for the complete observation years from 2019 to 2024 (Figure 10). The area-weighted annual mean remained relatively similar between 2019 and 2021, with values of 24.1 μmol m^{−2} in 2019, 23.9 μmol m^{−2} in 2020, and 23.8 μmol m^{−2} in 2021. Higher mean values were observed in 2022 (25.2 μmol m^{−2}), 2023 (25.9 μmol m^{−2}), and 2024 (29.2 μmol m^{−2}). These results demonstrate interannual variability and a distribution shifted toward higher tropospheric NO₂ column densities in 2024 relative to 2019. However, the six-year time series does not by itself establish a monotonic long-term trend or identify the processes responsible for the observed differences.

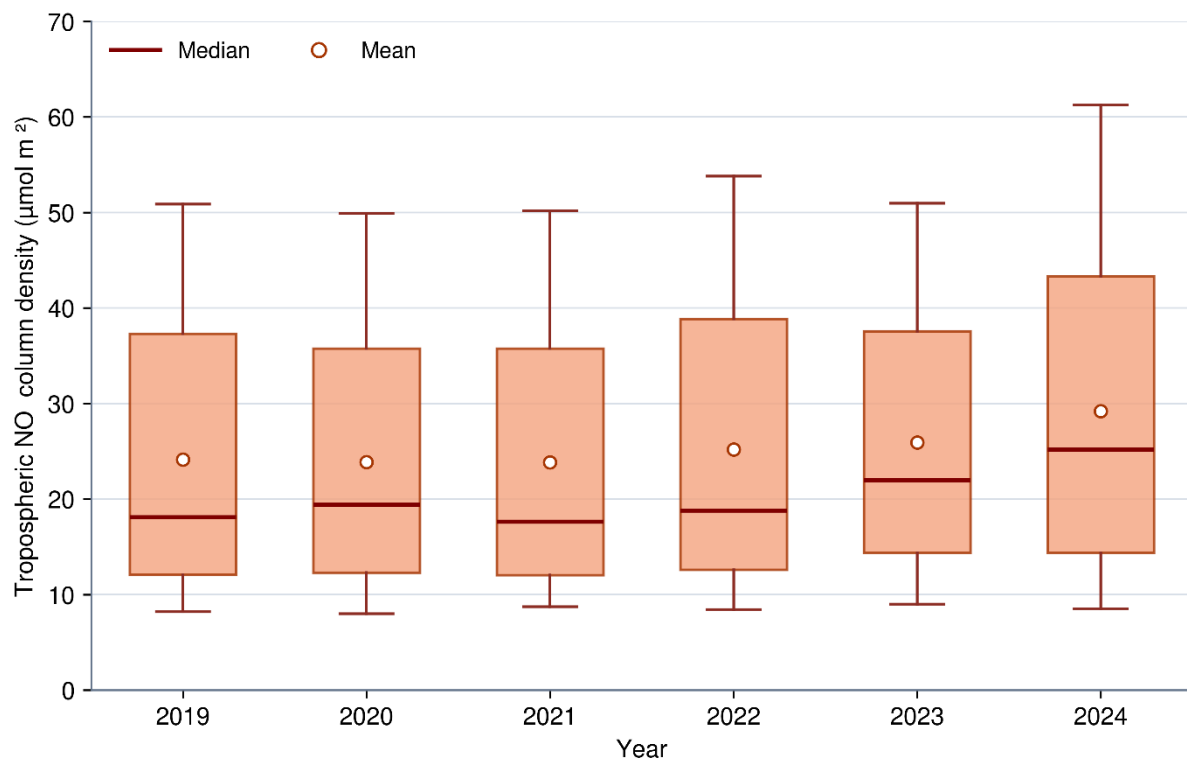


Figure 10. Annual distributions of tropospheric NO₂ column density over the WSF-derived built-up footprint within East Kazakhstan Region from 2019 to 2024.

5. Discussion

This study combined land-cover classification, cropland observations, settlement-detection data, and satellite-derived tropospheric NO₂ column densities within a common regional framework for East Kazakhstan. The individual datasets cover different spatial and temporal scales and describe distinct components of regional environmental change. Their integration enables a comparative spatial assessment, but it does not by itself demonstrate causal relationships between agricultural development, settlement expansion, industrial activity, and atmospheric NO₂.

5.1. Agricultural Development and Land-Use Change

The cropland extent increased from 4771.6 km² in 2003 to 5043.9 km² in 2019, corresponding to a net increase of 272.3 km² or 5.7%. The five observation epochs indicate expansion between 2003 and 2015, followed by a slight decrease of approximately 15.0 km² between 2015 and 2019. The temporal pattern should therefore be interpreted as a modest net expansion rather than a continuous annual increase.

The concentration of cropland in the northwestern and western lowlands reflects the spatial persistence of established agricultural areas. Cropland gains were frequently located adjacent to existing cropland, while the losses were more fragmented. This pattern indicates that most mapped changes occurred along the margins of established agricultural zones rather than through a large-scale relocation of agricultural activity.

Post-Soviet cropland abandonment and subsequent recultivation have been documented in other parts of Kazakhstan, particularly in the former Virgin Lands region [44]. However, the present analysis did not include agricultural policies, farm-level statistics, crop production, land ownership, or socio-economic variables. The observed changes in East Kazakhstan therefore cannot be attributed directly to post-Soviet agricultural recovery, policy reforms, or agricultural intensification. Such explanations remain hypotheses requiring dedicated socio-economic and agricultural data.

The cropland product represents conditions at five four-year observation epochs rather than a continuous annual record. Consequently, short-term cultivation cycles, temporary fallow land, crop rotations, and changes occurring within the intervals may not be represented. The detected net changes should therefore be interpreted as differences between the available observation epochs.

5.2. Built-Up Area Expansion and Associated Land-Cover Change

The harmonized WSF time series showed an increase in the detected built-up area within all nine settlement analysis windows between 1985 and 2025. Öskemen exhibited the largest absolute increase, followed by Ridder and Altai. However, these values refer to fixed rectangular analysis windows and should not be interpreted as official municipal-area statistics.

Interpretation of the temporal trajectories must account for the transition between the two WSF products. WSF Evolution provides Landsat-based detections at approximately 30 m resolution through 2015, whereas the post-2016 WSF Tracker observations are based primarily on Sentinel-1 and Sentinel-2 data at approximately 10 m resolution. The finer spatial resolution reduces mixed-pixel effects and changes the representation of fragmented settlement structures. Consequently, differences in the slopes before and after 2015 partly reflect the product and sensor transition and cannot be interpreted solely as changes in the rate of urban development.

The land-cover association analysis showed that grassland was the largest non-built class spatially associated with WSF detections during each of the five periods. Across 2000–2024, 13.31 km² of grassland, 4.61 km² of dense shrubs, and 1.15 km² of rainfed cropland were associated with newly detected built-up pixels. Sparse vegetation and dense vegetation accounted for 0.16 and 0.33 km², respectively.

These values differ substantially from the original estimates because the former first interval combined WSF detections from 1985 to 2004. Restricting the first period to 2000–2004 resulted in temporally comparable five-year intervals. The analysis also excluded pixels already classified as built-up area in the corresponding land-cover layer. The reported values therefore characterize only the five selected non-built classes and do not represent the total area of WSF detections.

The spatial overlays identify the land-cover labels associated with WSF detection periods, but they do not independently confirm physical land conversion. Differences in spatial resolution, classification definitions, acquisition dates, and detection methods between WSF and the land-cover products may contribute to individual class assignments.

5.3. Tropospheric NO₂ Patterns over Built-Up Areas

The annual Sentinel-5P composites showed recurring areas of elevated tropospheric NO₂ column density in northwestern East Kazakhstan, with the most pronounced spatial maximum around Öskemen. This spatial pattern is consistent with the concentration of settlements and industrial facilities in this part of the region. Previous studies have identified Ust-Kamenogorsk as an area of important industrial air-quality concern and have documented substantial contributions from industrial and energy-sector emissions in Kazakhstan [15].

Nevertheless, the Sentinel-5P analysis does not distinguish between industrial facilities, power generation, transportation, residential heating, transported pollution, and meteorological influences. The spatial correspondence between elevated NO₂ and urban–industrial areas therefore does not demonstrate that settlement expansion caused the observed NO₂ distribution.

Within the static WSF-derived built-up footprint, the area-weighted mean NO₂ column density remained similar between 2019 and 2021 and increased during 2022–2024. The mean increased from 24.1 $\mu\text{mol m}^{-2}$ in 2019 to 29.2 $\mu\text{mol m}^{-2}$ in 2024, while the median increased from 18.1 to 25.2 $\mu\text{mol m}^{-2}$. The endpoint differences correspond to increases of 21.0% and 39.0%, respectively. However, the intervening annual values do not constitute a continuous monotonic increase.

The higher values in 2024 may reflect changes in emissions, meteorological conditions, atmospheric transport, retrieval conditions, or a combination of these factors. Because meteorological variables and emission inventories were not included, the present analysis cannot distinguish among these possible explanations. A longer time series and statistical models incorporating wind, temperature, boundary-layer height, precipitation, heating demand, industrial production, and traffic would be required for source attribution and trend assessment.

The satellite product represents tropospheric NO₂ column density rather than ground-level concentration or personal exposure. Consequently, the results cannot be compared directly with regulatory surface-air thresholds or used independently to infer health effects. Regional studies based on ground observations and emission statistics provide important complementary evidence regarding air-quality and health concerns in industrial areas of East Kazakhstan [15,16], but those findings should remain analytically distinct from the Sentinel-5P results presented here.

5.4. Integrated Environmental Interpretation

The combined datasets identify northwestern East Kazakhstan as the part of the study region where settlement development, agricultural land, industrial centers, and elevated satellite-derived NO₂ values occur in relatively close spatial proximity. This co-location makes the area a priority for integrated environmental monitoring.

However, spatial overlap should not be equated with quantitative coupling. The study did not apply multivariate regression, causal inference, source-apportionment methods, or atmospheric transport modeling. It therefore cannot determine whether settlement expansion, industrial production, agricultural change, meteorology, or other factors explain the observed NO₂ differences.

The principal contribution of the integrated framework is the consistent spatial comparison of several independently derived Earth observation products. It provides a regional baseline, identifies locations and periods requiring further investigation, and highlights where ground-based observations and process-oriented analyses would be most informative.

5.5. Limitations and Future Research

Several limitations affect the interpretation of the results. First, the land-cover classifier was trained and validated using reference samples distributed across Kazakhstan. Although the independent hold-out validation produced an overall accuracy of 90.17% and a Cohen's kappa coefficient of 0.892, these metrics describe the broader classification model and not a separate East Kazakhstan-specific validation. Class-level errors may therefore differ within the study region.

Second, the cropland dataset is available for five observation epochs rather than as a continuous annual time series. Changes within the four-year intervals and temporary agricultural states cannot be resolved.

Third, the WSF time series combines two products with different sensors, spatial resolutions, and processing strategies. WSF Evolution is Landsat-based and provides approximately 30 m observations through 2015, whereas WSF Tracker uses Sentinel observations at approximately 10 m resolution after 2016. Although the products were

harmonized using the 2015 baseline and the July 2016 initialization mask, the resulting time series is not sensor-homogeneous. Moreover, the WSF indicates the first detected built-up signal rather than a verified construction date.

Fourth, the settlement statistics were calculated within fixed rectangular analysis windows rather than administrative city boundaries. The resulting areas support consistent temporal comparisons but should not be interpreted as official municipal built-up areas.

Fifth, the land-cover association analysis combines independently produced datasets with different classification schemes and spatial resolutions. It identifies spatial associations but does not verify individual land-conversion events.

Sixth, the Sentinel-5P record is short. The 2018 composite begins in May and was excluded from the quantitative interannual comparison, leaving six complete years from 2019 to 2024. This period is insufficient for establishing a robust long-term trend or detecting statistically reliable structural breaks. The study also evaluated only tropospheric NO₂ and therefore does not provide a comprehensive assessment of atmospheric pollution. Other relevant pollutants and atmospheric indicators, including particulate matter, sulfur dioxide, carbon monoxide, formaldehyde, methane, and aerosols, were not analyzed.

Seventh, Sentinel-5P measures tropospheric column density at a considerably coarser spatial resolution than the land-cover and WSF products. Individual emission sources cannot be resolved, and the satellite observations do not directly represent surface-level exposure. Ground measurements, emission inventories, meteorological observations, and atmospheric dispersion models would be required for source attribution and exposure assessment.

Finally, the study did not quantitatively distinguish between possible drivers such as land policy, privatization, mining development, agricultural programs, topography, meteorology, and atmospheric circulation. Future research should combine the Earth observation time series with socio-economic, industrial, policy, topographic, and meteorological variables using trend tests, change-point analyses, regression models, and spatially explicit causal frameworks.

6. Conclusions

This study presented an integrated Earth observation-based framework for describing land cover, cropland dynamics, settlement development, land-cover associations with newly detected built-up areas, and tropospheric NO₂ patterns in East Kazakhstan. The analysis combines datasets with different spatial and temporal characteristics and provides a regional baseline rather than a causal model of environmental change.

The regional land-cover classification showed that grassland was the largest class, covering 39.3% of the study region, followed by dense vegetation at 16.2%, rock at 14.9%, sparse vegetation at 10.6%, and bare soil at 7.4%. Independent hold-out validation of the classification model resulted in an overall accuracy of 90.17% and a Cohen's kappa coefficient of 0.892. The cropland analysis showed a net increase in mapped cropland extent between 2003 and 2019 from 4771.6 km² in 2003 to 5043.9 km² in 2019, corresponding to a net increase of 272.3 km² or 5.7%. Expansion occurred principally before 2015 and was followed by a minor decrease between 2015 and 2019.

The harmonized WSF analysis identified increasing built-up extent within all nine settlement windows between 1985 and 2025, with the largest absolute increase observed in Öskemen. Among the five non-built land-cover classes examined for 2000–2024, newly detected WSF pixels were most frequently associated with grassland, followed by dense shrubs and rainfed cropland.

Annual Sentinel-5P observations identified elevated tropospheric NO₂ column densities in northwestern East Kazakhstan, particularly around Öskemen. Within the static

WSF-derived built-up footprint, the area-weighted mean increased from $24.1 \mu\text{mol m}^{-2}$ in 2019 to $29.2 \mu\text{mol m}^{-2}$ in 2024, while the median increased from 18.1 to $25.2 \mu\text{mol m}^{-2}$.

The study's principal scientific contribution is the spatially consistent integration of independently derived Earth observation products for a region where environmental datasets remain fragmented. The framework identifies broad spatial patterns, quantifies selected changes, and provides reproducible reference information for subsequent process-oriented research.

Future work should incorporate regionally distributed validation samples, ground-based air-quality measurements, additional atmospheric pollutants, emission inventories, meteorological observations, and socio-economic and policy variables. Longer and more homogeneous time series would enable formal trend testing, change-point detection, regression analysis, and more reliable evaluation of the mechanisms underlying environmental change in East Kazakhstan Region.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/land15081513/s1>, Table S1. Datasets used for integrated analyses. Figure S1. Confusion matrix for the random forest land-cover classification based on the stratified hold-out validation subset ($n = 956$, 80:20 split from total 4780 reference points). (a) Confusion matrix showing the number of validation samples for each reference and predicted class. (b) Class-specific user's accuracy (precision), producer's accuracy (recall), and F1 score. (c) Overall accuracy, Cohen's kappa coefficient, and macro-averaged F1 score. Figure S2. Spatial distribution of estimated settlement-detection periods within built-up areas in major settlements of East Kazakhstan. Figure S3. Annual NO_2 concentrations for East Kazakhstan between 2019 and 2023.

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