

War, economic activity, and spatial inequality: Evidence from Nighttime lights in Ukraine[☆]

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ABSTRACT

The Russian invasion of Ukraine in 2022 caused an unprecedented economic shock, yet reliable measures of economic activity during wartime are scarce, particularly at the subnational level. Official GDP statistics are available only at the national level and with substantial delays, while systematic evidence remains limited on how the war affected economic activity across regions. This paper provides a nationwide subnational assessment of the economic impact of the war in Ukraine by exploiting satellite-based nighttime light data as a proxy for local economic activity.

Using annual VIIRS Day/Night Band data for the period 2014–2024, we analyze changes in nighttime light intensity across Ukrainian districts and relate them to geographic exposure to armed conflict events recorded by ACLED. We estimate two-way fixed effects models that exploit within-district variation over time and spatial variation in distance to conflict locations following the escalation of the war in 2022. Because distance to conflict is not exogenously assigned, the estimates are interpreted as spatial associations rather than causal effects. At the national level, we document a strong correlation between official GDP and nighttime lights, supporting the validity of the proxy in the Ukrainian context.

Our results reveal a pronounced spatial gradient in wartime economic disruption. Districts located closer to conflict events experienced significantly larger declines in nighttime-light intensity after 2022. The continuous specification shows that these declines attenuate with distance, while the categorical estimates suggest that the relative difference increases up to approximately 25–50 km and changes little beyond that range. These findings highlight the localized nature of wartime changes in observed nighttime activity and underscore the value of satellite data for examining economic dynamics in settings characterized by data gaps, conflict, and institutional disruption.

Introduction

The Russian invasion of Ukraine in 2022 has generated a severe economic shock, with profound consequences for economic activity within the country. Recent evidence also points to substantial macro-economic spillovers, with the war imposing large costs on the global economy and particularly severe contractions across Europe (e.g., Tank & Ospanova, 2022). While the aggregate effects of the war have been widely discussed, much less is known about how its economic impact varies within the country. The conflict has been highly uneven in its geographic intensity, with some regions experiencing direct military

activity, infrastructure destruction, and population displacement, while others have remained relatively distant from active combat. Understanding this spatial heterogeneity is crucial for identifying which areas have been most affected in terms of economic contraction and which have shown greater resilience, providing key insights for both economic analysis and post-conflict reconstruction (Abadie & Gardeazabal, 2003). The impact of war on economic performance is not straightforward. While conflict often leads to substantial economic losses, its effects can be heterogeneous across regions and may even be locally positive in certain contexts, as shown by Sevastianova (2009).

Answering this question is challenging due to severe data limitations;

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empirical evidence on the spatial economic effects of the war remains limited. Existing assessments rely heavily on national-level GDP estimates produced by international organizations such as the International Monetary Fund. While these figures provide a useful aggregate benchmark, they conceal substantial within-country variation and offer no information on how economic activity has evolved across regions and cities. The lack of subnational data is particularly problematic in a context of active conflict, where statistical systems are disrupted and timely regional accounts are unavailable. As a result, there is currently no systematic evidence on which areas of Ukraine have experienced the largest economic declines and how these effects relate to local exposure to conflict.

This paper addresses this gap by providing a nationwide subnational assessment of the economic impact of the war in Ukraine. In the absence of reliable regional GDP statistics, we exploit satellite-observed nighttime light intensity as a proxy for local economic activity. A growing literature shows that nighttime lights closely track economic output, particularly in environments characterized by weak institutions, conflict, or data scarcity (Henderson, Storeygard, & Weil, 2012; Pinkovskiy & Sala-i-Martin, 2016). In the Ukrainian context, satellite data offer a unique advantage: they provide consistent, spatially detailed, and timely information that is unaffected by wartime disruptions to administrative reporting.

We combine annual nighttime light data from the VIIRS Day/Night Band with georeferenced information on armed conflict events from the Armed Conflict Location & Event Data Project (ACLED). The analysis covers the period 2014–2024, allowing us to account for the earlier phase of conflict in Eastern Ukraine and to isolate the economic effects associated with the large-scale invasion that began in 2022. Nighttime light intensity is aggregated at the district level, while conflict exposure is measured using geographic distance to recorded violent events, capturing differential local exposure to warfare.

Our empirical strategy exploits within-district variation over time using two-way fixed effects models with district and year fixed effects. Identification relies on differential changes in nighttime light intensity after 2022 across districts located at varying distances from conflict locations. We implement both continuous distance-decay specifications and flexible distance-bin models to allow for non-linear spatial effects and to avoid imposing restrictive functional form assumptions. Before turning to subnational analysis, we validate the use of nighttime lights in the Ukrainian context by documenting a strong correlation between national GDP and aggregate nighttime light intensity in the post-2013 period.

The results reveal a highly localized pattern of economic disruption. Districts located closer to conflict events experienced substantially larger declines in nighttime light intensity following the 2022 invasion, while economic losses attenuate rapidly with distance and become economically and statistically small beyond approximately 50 km. This spatial pattern suggests that wartime economic damage is concentrated near active conflict zones, with limited spillovers to more distant districts.

This paper makes three main contributions. First, it provides a nationwide subnational assessment of economic activity in Ukraine during the ongoing war, filling a critical gap in a context where official regional GDP data are unavailable and national aggregates conceal substantial spatial heterogeneity. Second, by combining satellite-based nighttime lights with georeferenced conflict data, it contributes to the growing literature that uses non-traditional data sources to measure economic activity during global crises, armed conflict, and institutional disruption (Henderson et al., 2012; Donaldson & Storeygard, 2016; Michalopoulos & Papaioannou, 2013). Third, the paper sheds light on the spatial economic footprint of war, documenting a sharp and localized decay of economic losses with distance to conflict, thereby informing debates on economic fragmentation, resilience, and post-conflict reconstruction in a globalized economy (Collier, 2008; Rohner, Thoenig, & Zilibotti, 2013). More broadly, the findings

illustrate how global geopolitical shocks translate into highly uneven local economic outcomes, with important implications for regional policy and international recovery efforts. Because distance from conflict is not exogenously assigned, these estimates are interpreted as conditional spatial associations rather than causal effects.

The remainder of the paper is organized as follows. Section 0 provides an overview of Ukraine's war economy, with a focus on how the conflict has affected economic activity across regions and over time. Section 0 describes the data sources and the construction of the main variables, including nighttime light intensity and measures of conflict exposure. Section 0 outlines the empirical strategy used to estimate the relationship between conflict proximity and local economic dynamics. Section 0 presents the main results, with particular attention to nighttime-light resistance and adaptive recovery across districts. The final section concludes.

Regional ukrainian's war economy

Ukraine has long been characterized by substantial regional disparities in economic activity, reflecting differences in industrial structure, geographic location, and integration into domestic and international markets. Prior to the 2022 invasion, economic output in Ukraine was highly concentrated in a limited number of regions. The capital city of Kyiv alone accounted for approximately 24% of national gross regional product, highlighting a strong degree of economic centralization. In addition, a small group of industrial and metropolitan regions, including Dnipropetrovsk, Kharkiv, Kyiv oblast, and Odesa, collectively contributed more than half of total economic output (Huk & Zeynalov, 2022). In contrast, several western and peripheral regions exhibited significantly lower levels of income and productivity, reflecting a more limited industrial base and weaker economic integration. For example, regions such as Ternopil, Zakarpattia, and Chernivtsi each accounted for only around 1–2% of national output, while Luhansk contributed close to 1% prior to the full-scale invasion. These pre-existing disparities provide an important baseline for understanding how the war has reshaped the economic geography of the country (World Bank, 2020).

The large-scale invasion in February 2022 triggered a dramatic contraction in aggregate economic activity, with real GDP declining by approximately 29% in 2022 (International Monetary Fund (IMF), 2023; World Bank, 2023). However, aggregate indicators mask substantial spatial heterogeneity in the economic impact of the war. The intensity of military operations, destruction of infrastructure, and population displacement has varied widely across regions, leading to sharply differentiated local economic outcomes. Eastern and southern regions, including Donetsk, Luhansk, Kharkiv, Zaporizhzhia, and Kherson, have suffered extensive destruction of physical capital and infrastructure, resulting in large declines in industrial output and overall economic activity (World Bank, 2023; International Monetary Fund (IMF), 2023). By contrast, central and western regions have been relatively less exposed to direct conflict and, in some instances, have experienced more stable economic activity. This relative resilience is partly driven by the relocation of firms and workers from conflict-affected areas, as well as by the reorganization of domestic supply chains (Darvas, 2023).

These dynamics have contributed to a reconfiguration of Ukraine's economic geography. The war has accelerated a westward shift in economic activity, with regions such as Lviv, Ternopil, and Zakarpattia emerging as important destinations for internally displaced firms and populations. At the same time, Kyiv has maintained – and in some respects strengthened – its central role in the national economy, supported by its administrative functions, service sector concentration, and relatively lower exposure to sustained military operations (World Bank, 2024). This combination of severe contraction in frontline regions and relative resilience elsewhere implies a substantial widening of regional disparities.

Several studies have begun to document these subnational effects using nighttime lights and other unconventional data. Kochnev (2019)

examines the separatist-controlled areas of Donetsk and Luhansk following the onset of conflict in 2014 and finds substantial reductions in economic activity associated with separatist control and subsequent trade restrictions. Zhukov (2023) combines near-real-time information on violence and territorial control with satellite-based measures during the 2022 invasion, showing that observed activity declined most sharply in contested and heavily shelled urban areas. Constantinescu, Kappner, and Szumilo (2022) combine nighttime lights, Google Trends, and social-media activity to construct monthly measures of regional economic conditions during 2022. Behrens (2024), focusing on Russian border regions after 2014, further shows how conflict-related border changes and losses of market access can affect nighttime-light growth and manufacturing activity. The present study complements this literature by covering 139 Ukrainian districts over 2014–2024 and examining how post-2022 nighttime-light changes vary systematically with distance from recorded conflict locations.

Despite this growing literature, nationwide and consistently measured evidence below the regional level remains limited. Official statistics are primarily available at the national level, while regional accounts are either missing, delayed, or unreliable due to disruptions in data collection systems during the war. Existing evidence on regional disparities is therefore largely descriptive or focuses on selected regions, territories, or shorter periods, using partial indicators such as sectoral output, infrastructure damage assessments, or firm relocation data. This lack of consistent and comparable subnational measures represents a major obstacle to understanding the magnitude and spatial distribution of wartime economic disruption.

In this context, satellite-based nighttime light data provide a valuable tool for measuring economic activity at a fine geographic scale. Nighttime lights offer a consistent proxy for local economic intensity that is not affected by wartime disruptions to statistical systems and can be used to track changes in economic activity across regions and cities over time (Henderson et al., 2012; Donaldson & Storeygard, 2016). By exploiting spatial variation in exposure to conflict, these data make it possible to document how changes in observed nighttime activity vary across space and with distance from conflict locations. This approach is particularly well suited to the Ukrainian context, where understanding the spatial heterogeneity of wartime economic impacts is central to both academic analysis and policy design.

Data and variables

This section describes the data sources used to measure economic activity and conflict exposure, as well as the construction of the main variables used in the empirical analysis.

Nighttime lights

We use satellite-based nighttime light intensity as a proxy for local economic activity. Specifically, we rely on annual data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB), which provides global observations of light emissions at high spatial resolution.

To ensure comparability over time and reduce measurement noise, we use yearly median-masked composites. The production process filters observations affected by sunlight, moonlight, clouds, and background noise and applies outlier removal to reduce contamination from biomass burning and other transient sources (Elvidge, Zhizhin, Ghosh, Hsu, & Taneja, 2021). These procedures substantially reduce ephemeral light, but they do not guarantee the removal of all conflict-related illumination. Nighttime light data have been widely used in the literature as a proxy for economic activity, particularly in settings with data limitations or institutional disruption (Chen & Nordhaus, 2011).

Raster data are aggregated at the district level (administrative level 2) using area-weighted averages. The analysis covers the period 2014–2024, with robustness checks restricting the sample to the post-

2018 period. The starting year, 2014, coincides with the onset of armed conflict in Eastern Ukraine and represents the earliest period in which nighttime lights plausibly reflect conflict-adjusted economic conditions. The shorter 2018–2024 window provides four recent pre-invasion observations and excludes the more unstable initial phase of the conflict. We also examine whether the estimates are sensitive to starting the sample in alternative years.

The dependent variable is defined as:

$$y_{it} = \log(\text{Mean Nighttime Lights}_{it} + 1)$$

where *i* indexes cities and *t* indexes years. The logarithmic transformation reduces skewness and allows for an interpretation of coefficients in percentage terms. Summary statistics of the variables used in the analysis are shown in Table 1 below.

An important caveat when using nighttime lights in a conflict setting concerns the interpretation of light intensity in areas exposed to active military operations. In such contexts, observed luminosity may reflect not only civilian economic activity but also conflict-related sources of light, including fires, explosions, and military infrastructure. This issue is particularly relevant in locations experiencing high-intensity violence, where these additional light emissions may attenuate or partially mask underlying declines in economic activity. At the same time, a large body of evidence shows that nighttime lights remain a reliable proxy for broad economic dynamics, especially when analysis focuses on relative changes across locations and over time. In this study, the use of spatial and temporal variation in luminosity, together with measures of conflict exposure, allows us to extract meaningful information on local economic activity while acknowledging these measurement limitations. Conflict intensity is generally associated with larger declines in nighttime lights between 2021 and 2022. However, seven districts in the top decile of conflict exposure experienced declines that were smaller than the national municipal average, although none recorded stable or increasing luminosity. These cases are reported in Appendix Fig. A1 and Appendix Table A1 and are examined further in the robustness analysis.

Armed conflict events

Information on armed conflict is obtained from the Armed Conflict Location & Event Data Project (ACLED), which provides georeferenced records of conflict events, including shelling, missile attacks, and other forms of remote violence.

We use the geographic location of these events to construct a measure of conflict exposure for each district. Specifically, for each district we compute the minimum geodesic distance to any recorded conflict event using spatial point-to-polygon distance measures. This approach captures the proximity of each district to areas affected by violence.

In the exploratory resistance and adaptive-recovery analysis, conflict severity is measured using the cumulative number of recorded events during 2022–2024. We use cumulative fatalities over the same period as an alternative indicator. Event counts capture the frequency of recorded violent incidents, whereas fatalities provide a complementary measure of their severity. Because both measures may be affected by reporting conditions during active conflict, they are interpreted as alternative indicators rather than exact measures of total conflict exposure.

Table 1
Summary Statistics.

Variable	Mean	SD	Min	Max	N
Log Nighttime Lights	0.245	0.398	0.000	3.633	1529
Log Distance to Conflict	2.659	0.818	0.221	4.469	139
Conflict events, 2022–2024	1146.63	2923.35	1	18,579	139

Measures of conflict exposure

Our empirical strategy relies on variation in geographic exposure to conflict across cities. To this end, we construct a time-invariant measure of distance to conflict, defined as the minimum distance between each district and the set of conflict events observed over the study period. This measure captures persistent spatial exposure to conflict intensity, abstracting from short-term fluctuations in conflict lines.

We consider two alternative specifications.

First, we define a continuous measure of distance:

$$\text{Log distance}_i = \ln(1 + d_i),$$

where d_i is the minimum distance in kilometres between district i and a recorded conflict location. The addition of one permits the inclusion of districts located very close to conflict events. This specification allows us to estimate a continuous spatial decay in the post-2022 nighttime-light gradient.

Second, we construct discrete distance categories to enable a flexible, nonparametric assessment of spatial patterns. Districts are grouped into the following bins: 0–10 km (reference category), 10–25 km, 25–50 km, and 50–100 km.

This approach avoids imposing a specific functional form on the relationship between distance and economic outcomes and allows for potential non-linearities in the spatial decay of conflict effects. The categories facilitate interpretation but necessarily discard variation in distance within each interval. For this reason, the continuous specification is treated as the primary model and the distance-bin specification as a complementary analysis.

Empirical strategy

The empirical analysis exploits variation in geographic exposure to conflict across districts to examine how nighttime-light intensity changed following the escalation of war in 2022. The baseline approach compares changes in nighttime light intensity before and after the onset of the full-scale invasion across locations with different proximity to conflict events. Following the general approach used in studies of the spatial consequences of conflict, including [Abadie and Gardeazabal \(2003\)](#) and [Besley and Mueller \(2012\)](#), we estimate whether post-2022 changes in nighttime lights vary systematically with conflict proximity:

$$y_{it} = \beta(\text{Post}_t \times \log(\text{Distance}_i + 1)) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where Post_t equals 1 for years 2022 onward; i indexes districts and t indexes years, d_i is the minimum distance between district i and recorded conflict locations, α_i are district fixed effects controlling for time-invariant local characteristics, such as geography, pre-war economic structure, and infrastructure; λ_t are year fixed effects capturing aggregate shocks common to all districts, including nationwide macroeconomic trends. Standard errors are clustered at the district level.

The coefficient β measures whether the post-2022 change in nighttime-light intensity varies systematically with distance from conflict. A positive coefficient indicates that districts located farther from conflict areas experienced relatively smaller declines, or stronger increases, in nighttime lights. Because distance is time invariant, the model combines within-district changes in nighttime lights with between-district differences in distance from conflict. It does not exploit changes in distance within the same district.

To allow for a more flexible characterization of spatial patterns, the analysis also considers a specification based on discrete distance categories:

$$y_{it} = \sum_k \beta_k (\mathbb{I}[\text{Distance}_i \in k] \times \text{Post}_t) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where D_k indexes distance bin k and districts located within 0–10 km

from conflict events serve as the reference category.

This specification does not impose a functional form on the relationship between distance and nighttime-light changes and allows for the identification of non-linearities in the spatial gradient associated with conflict proximity. However, grouping districts into a small number of distance intervals discards variation within each category. The continuous-distance model is therefore treated as the primary specification, while the distance-bin model provides a complementary and more readily interpretable description of possible non-linearity.

Distance from conflict is not randomly or exogenously assigned. Districts nearer to conflict locations may differ from more distant districts in their industrial structure, infrastructure, population, political history, or strategic importance. District fixed effects absorb time-invariant differences in these characteristics, and year fixed effects absorb common national shocks, but the models cannot rule out differential time-varying factors correlated with conflict proximity. Therefore, the estimates are interpreted as conditional spatial associations rather than as causal effects of distance from conflict.

To assess whether the post-2022 gradient may reflect trajectories that were already present before the full-scale invasion, we estimate a separate pre-period model using only observations from 2018 to 2021. In this model, a linear time trend is interacted with log distance, while district and year fixed effects are retained. We also estimate year-specific distance interactions relative to 2021 to describe when the spatial gradient emerged. The linear pre-period trend test is reported in Appendix Table A2, while the year-specific estimates are shown in Appendix Fig. A2. The latter is used as a descriptive timing exercise rather than as a formal causal event-study design.

Additional sensitivity analyses vary the first year of the estimation sample from 2014 to 2019 and exclude Crimea, the most conflict-intensive districts, and the highly exposed districts with comparatively moderate nighttime-light declines identified in Appendix Table A1.

While the baseline specifications capture the average association between conflict proximity and changes in nighttime lights, the following resistance–recovery analysis constitutes a separate exploratory empirical strategy rather than an extension of Eqs. (1) and (2). Districts may differ substantially in their ability to absorb and adapt to wartime shocks. Some districts experience persistent declines in nighttime lights, whereas others exhibit stabilization or partial recovery despite continued exposure to conflict.

To capture these heterogeneous responses, a district-level measure of nighttime-light resistance and adaptive recovery is constructed based on the regional resilience framework proposed by [Martin \(2012\)](#). In this framework, resilience is defined relative to the national trajectory and reflects how strongly a region responds to an adverse shock compared with the aggregate economy.

The key idea is to evaluate local nighttime-light performance in relative rather than absolute terms. Districts that experience larger declines than the national average are considered more sensitive to the shock, while those with smaller declines exhibit greater resistance.

In the original formulation, resilience is measured using employment data. Given the lack of reliable subnational employment or GDP data during the war, we adapt the framework using nighttime-light intensity. The resulting measures should be interpreted as descriptive indicators of relative nighttime-light dynamics rather than as direct measures of economic resilience, productive capacity, or welfare.

Let E_r denote employment in region r and E_N national employment. The sensitivity index is defined as: $\beta_r = \frac{\Delta E_r / E_r}{\Delta E_N / E_N}$, where $\Delta E / E$ denotes the percentage change during the shock period.

Given the lack of reliable subnational employment or GDP data during the war, this framework is adapted using nighttime light intensity as a proxy for economic activity, following a large literature validating its use in data-constrained environments ([Henderson et al., 2012](#); [Donaldson & Storeygard, 2016](#)).

Let $NTL_{i,t}$ denote average nighttime light intensity in district i at time

t.

Resistance captures the immediate response of each district to the escalation of the war in 2022. The district -level change in nighttime lights between 2021 and 2022 is defined as:

$$\Delta NTL_i = \frac{NTL_{i,2022} - NTL_{i,2021}}{NTL_{i,2021}}$$

The corresponding national change is:

$$\Delta NTL_N = \frac{NTL_{N,2022} - NTL_{N,2021}}{NTL_{N,2021}}$$

where NTL_N denotes national average nighttime light intensity.

The index is then computed as $\beta_i = \frac{\Delta NTL_i}{\Delta NTL_N}$. Values greater than one indicate that a district experienced a larger decline than the national average, implying lower resistance, while values below one indicate higher resistance to the shock.

To facilitate interpretation, the resistance index, denoted by β_i^R , is defined as the complement of β_i :

$$\beta_i^R = 1 - \beta_i \quad (3)$$

Under this transformation, higher values correspond to greater resistance to the wartime shock.

Because the war is ongoing, subsequent dynamics are interpreted as adaptive responses rather than post-conflict recovery. Adaptive recovery is defined as the relative change in nighttime lights following the initial shock.

The district -level change between 2022 and the most recent year 2024 is:

$$\Delta NTL_i^{Rec} = \frac{NTL_{i,2024} - NTL_{i,2022}}{NTL_{i,2022}}$$

The corresponding national change is:

$$\Delta NTL_N^{Rec} = \frac{NTL_{N,2024} - NTL_{N,2022}}{NTL_{N,2022}}$$

The adaptive recovery index is therefore:

$$\beta_i^{Rec} = \frac{\Delta NTL_i^{Rec}}{\Delta NTL_N^{Rec}} \quad (4)$$

Values greater than one indicate stronger stabilization or improvement in economic activity relative to the national trend, while values below one indicate weaker adaptive performance.

To summarize overall district economic resilience, a composite index is constructed by combining resistance and adaptive recovery. Both components are first standardized and then averaged:

$$\text{Resilience}_i = \frac{z(\beta_i^R) + z(\beta_i^{Rec})}{2} \quad (5)$$

where $z(\cdot)$ denotes standardization. The composite measure is used as an exploratory summary indicator and is not interpreted as a directly observed measure of local economic resilience.

Finally, we examine whether the three indicators are associated with conflict severity. The unadjusted models regress each indicator on the logarithm of conflict events or fatalities recorded during 2022–2024. The adjusted specification is:

$$Q_i = \gamma_0 + \gamma_1 \ln(1 + \text{Conflict}_i) + \gamma_2 y_{i,2021} + \gamma_3 \ln(1 + d_i) + \theta_r + u_i, \quad (6)$$

where Q_i denotes the resistance, adaptive-recovery, or composite indicator; Conflict_i is measured alternatively by recorded events and fatalities; $y_{i,2021}$ is pre-invasion log nighttime-light intensity; and θ_r denotes oblast fixed effects. Heteroskedasticity-robust standard errors are reported. These cross-sectional regressions remain descriptive. Conflict intensity may itself be related to the prior economic or strategic importance of a district, so the controls do not eliminate concerns about

reverse causality or omitted variables.

Results

The empirical analysis proceeds in a sequence of steps. The first part evaluates the relationship between official GDP statistics and nighttime lights to validate the use of luminosity as a proxy for economic activity. The core results then examine how wartime nighttime-light change vary with distance from conflict locations. The section then turns to heterogeneity in district -level responses using a resistance-recovery framework.

Nighttime lights and GDP

The first analysis examines the relationship between national GDP and nighttime light intensity in Ukraine after 2013. Table 2 reports both Pearson and Spearman correlations between the two variables.

Both correlation measures indicate a strong association between official economic output and satellite-observed nighttime lights. For the full 2014–2024 period, the Pearson and Spearman correlations are 0.898 and 0.891, respectively. The association is particularly strong before 2022 but becomes slightly weaker in the broader 2020–2024 period, which includes both the pandemic and the full-scale invasion. The strength of this relationship is notable given the substantial institutional disruptions and economic shocks experienced during the study period.

The five-year rolling correlations reported in Appendix Fig. A3 show that the relationship remains positive throughout the period but becomes less stable in windows that include 2022. Appendix Fig. A4 similarly shows that standardized GDP and nighttime-light series follow broadly comparable trajectories through 2021 but diverge to some extent thereafter. This evidence supports the use of nighttime luminosity as a proxy for economic activity in Ukraine while also indicating that the relationship is not invariant during exceptional periods. The remainder of the analysis therefore relies on nighttime light data to investigate spatial economic dynamics at the district level. Satellite observations provide annual measurements at fine spatial resolution, allowing the analysis to capture localized war impacts that are not observable in official statistics.

Distance to conflict and spatial gradients of economic disruption

The core analysis examines how changes in nighttime lights vary with distance from conflict locations. Two complementary specifications are used: a continuous distance model (eq. 1) and a distance-bin model (eq. 2). The empirical strategy identifies differential exposure to conflict based on geographic proximity to recorded events. Distance to conflict is interpreted as a measure of local exposure rather than an exogenous source of variation. While district fixed effects control for time-invariant differences across locations and year fixed effects absorb common

Table 2
Correlation between GDP and nighttime lights in Ukraine.

Period	Years	N	Pearson correlation	Spearman correlation
Full period	2014–2024	11	0.898	0.891
Pre-pandemic period	2014–2019	6	0.845	0.829
Pandemic and war period	2020–2024	5	0.702	0.700
Before the full-scale invasion	2014–2021	8	0.930	0.929
Full-scale invasion period	2022–2024	3	0.987	1.000

Notes: Correlations for 2022–2024 are descriptive because the subperiod contains only three annual observations. Statistical inference is therefore not reported for this subperiod.

shocks, the estimates should be interpreted as capturing spatial patterns of economic disruption associated with conflict exposure rather than causal effects of conflict placement.

Continuous distance models

The continuous specifications estimate the interaction between the post-war period (from 2022 onward) and the logarithm of distance to conflict events. Table 3 reports the results for two time windows: the full sample period (2014–2024) and a narrower period (2018–2024), the latter used as a robustness check.

The coefficients are positive and statistically significant in both specifications, indicating that districts located farther from conflict events experienced smaller declines in nighttime light intensity after 2022. Given the logarithmic specification, the interaction coefficient represents the post-2022 differential elasticity of nighttime lights with respect to distance. A 1% increase in distance to the nearest conflict event is associated with an approximately 0.051% smaller decline in nighttime lights in the 2014–2024 specification and a 0.050% smaller decline in the 2018–2024 specification. To provide a more intuitive interpretation, consider a doubling of distance to conflict. Since a doubling corresponds to an increase of approximately 0.693 in log distance, the estimates imply that doubling the distance to the nearest conflict event is associated with about a 3.5% smaller decline in nighttime lights. These magnitudes are comparable to those reported by Abadie and Gardeazabal (2003), who document that per capita GDP in the Basque Country declined by approximately 10 percentage points relative to a synthetic control region following the onset of terrorism.

A pre-period test using only 2018–2021 observations provides no evidence that nighttime-light trajectories already varied systematically with distance. The estimated interaction between a linear trend and log distance is 0.0019 and statistically insignificant ($p = 0.354$; Appendix Table A2). Appendix Fig. A2 provides complementary descriptive evidence: year-specific distance coefficients remain close to zero during most of the immediate pre-invasion period and become positive from 2022 onward.

The result is also insensitive to the choice of starting year. Appendix Table A3 shows that the coefficient remains between 0.0487 and 0.0507 when the sample begins in any year from 2014 to 2019 and is statistically significant in every specification. The selection of 2018 as the starting year for the shorter specification therefore does not drive the estimated gradient.

Distance-bin models

As mentioned in Section 0, the distance-bin specification allows for a flexible, non-linear assessment of spatial decay. Districts located within 0–10 km of conflict events serve as the reference group. Table 4 reports results for two-time windows: 2014–2024 and 2018–2024.

The point estimates show that districts located beyond the immediate conflict zone experienced smaller post-2022 declines in nighttime lights than districts within 0–10 km of recorded conflict locations. The estimated difference increases from the 10–25 km category to the 25–50 km category and changes little beyond 50 km. The 25–50 km coefficient is statistically significant in both estimation periods, while the 50–100 km coefficient is significant only in the full 2014–2024 sample. The 10–25 km coefficient is positive but not statistically significant. Overall,

Table 3
Continuous distance models.

Time period	Coefficient (log distance $\times$ post) Std. error
2014–2024	0.051** (0.016)
2018–2024	0.050** (0.015)

Table 4
Distance-bin models.

Variable	2014–2024	2018–2024
0–10 km $\times$ post-2022	Reference	Reference
10–25 km $\times$ post-2022	0.0513 (0.0398)	0.0451 (0.0385)
25–50 km $\times$ post-2022	0.0903* (0.0412)	0.0918* (0.0380)
50–100 km $\times$ post-2022	0.0841* (0.0425)	0.0848 (0.0439)
District fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	1529	973
Within R^2	0.0275	0.0332

Notes: The dependent variable is log nighttime-light intensity. Districts located within 0–10 km of recorded conflict locations constitute the reference category. All models include district and year fixed effects. Standard errors clustered by district are reported in parentheses. * $p < 0.05$.

the categorical results are consistent with a localized spatial gradient, although the estimates are less precise than those from the continuous-distance specification.

Fig. 1 illustrates this pattern. The estimated coefficients increase between the 10–25 km and 25–50 km categories and remain similar in the 50–100 km category. The confidence intervals are relatively wide, particularly for the outer distance category, so the figure is interpreted as evidence of the shape of the spatial gradient.

The estimated gradient is also robust to several sample restrictions. Excluding Crimea produces a coefficient of 0.0531. The estimate remains positive after removing districts in the top 5% and top 10% of conflict exposure, although it becomes less precise in the top-10% exclusion. When Crimea and the top 10% of conflict-exposed districts are excluded jointly, the coefficient is 0.0471 and remains statistically significant.

We additionally exclude the seven high-conflict districts identified in Appendix Table A1, all of which experienced smaller-than-average but still negative nighttime-light changes. In the 2018–2024 sample, the coefficient increases from 0.0498 to 0.0630 and remains statistically significant. These districts therefore do not account for the principal spatial gradient.

Exploratory Nighttime-light resistance and adaptive recovery

To examine variation in local responses to the wartime shock, the Martin resistance–recovery framework is applied to nighttime light data. The findings presented below relate to the broader literature on regional economic resilience (Martin & Sunley, 2015). The resistance index (eq. 3) measures the initial change in nighttime lights between 2021 and 2022 relative to the national trend. Adaptive recovery index (eq. 4) measures the subsequent change relative to the national trajectory.

The districts with the lowest and highest composite scores are reported in Appendix Tables A5 and A6. Low scores are concentrated primarily in areas exposed to sustained military activity, including Beryslavskiy, Kupianskiy, Khersonskiy, Kramatorskiy, Pokrovskiy, and Bakhmutskiy. Several of the highest scores occur in Crimea, where relative stability in observed luminosity should not be interpreted as post-war economic recovery.

The results are also reported in the maps in Figs. 2, 3 and 4 below. Darker colours indicate lower performance, while lighter colours indicate higher performance. The maps reveal a clear and consistent spatial pattern in the economic response to the 2022 shock. Initial resistance exhibits strong heterogeneity, with the lowest values concentrated in eastern and southern regions closer to conflict zones, while western regions display relatively higher resistance. Estimated resilience appears more spatially uniform, yet clusters of lower resilience persist in heavily

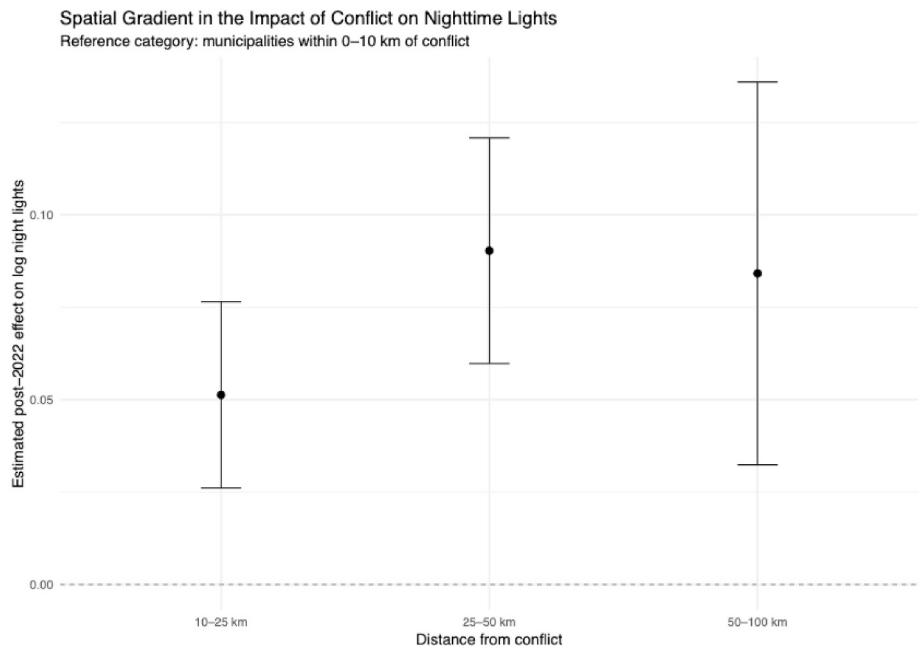


Fig. 1. Spatial gradient in the impact of conflict on nighttime lights.

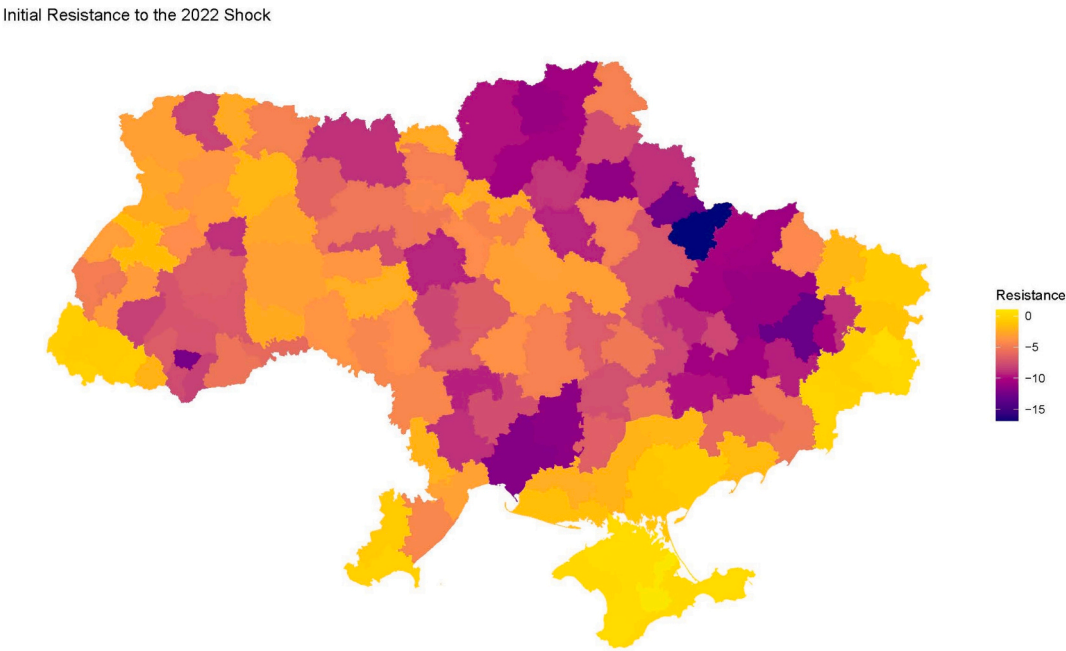


Fig. 2. Spatial distribution of nighttime-light resistance to the 2022 shock.

affected areas, indicating that initial vulnerabilities are not fully absorbed over time. Adaptive recovery remains uneven, with limited rebound in high-exposure regions and comparatively stronger recovery in more distant areas.

To examine whether conflict intensity is systematically related to the nighttime-light indicators, regression models were estimated using the logarithm of recorded conflict events and fatalities as explanatory variables. The results are shown in Table 5. They reveal a strong negative relationship between conflict intensity and the composite nighttime-light index. In the unadjusted models, both event counts and fatalities are associated with lower composite scores. The event-count coefficient remains negative and statistically significant after controlling for 2021 nighttime-light intensity, distance from conflict, and oblast fixed effects,

whereas the adjusted fatality coefficient is no longer statistically significant.

When the two components are examined separately, the results differ in robustness. Conflict intensity is negatively associated with resistance only in the unadjusted event-count model; the association becomes statistically insignificant after controls are included and is not reproduced when fatalities are used. By contrast, adaptive recovery is negatively associated with both conflict events and fatalities in the unadjusted and adjusted specifications. The relationship between conflict severity and the composite indicator therefore appears to be driven mainly by weaker subsequent nighttime-light recovery rather than by the initial resistance component.

These results suggest that conflict exposure is associated with spatial

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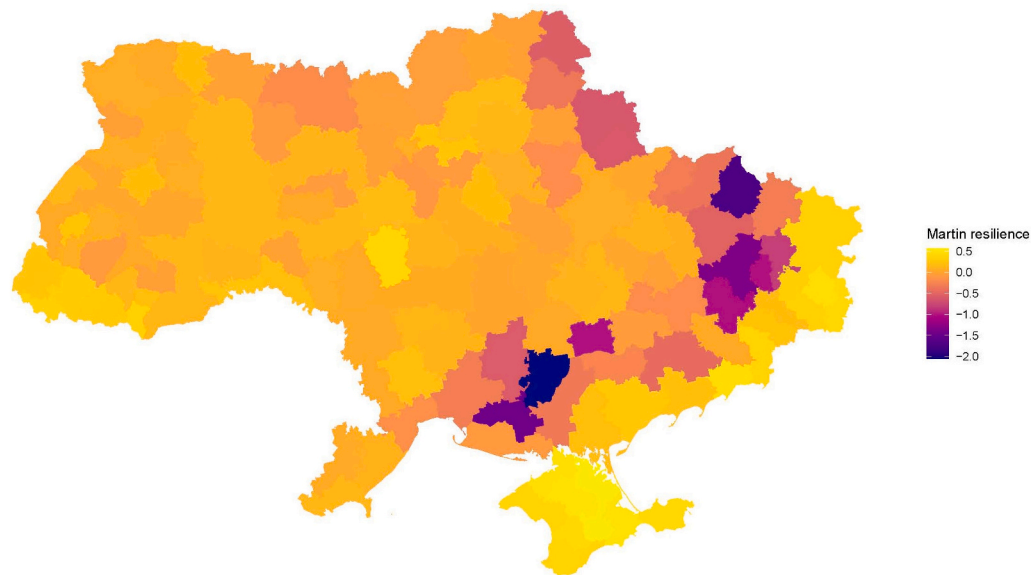


Fig. 3. Spatial distribution of the composite nighttime-light indicator.

Adaptive Recovery, 2022 to 2024

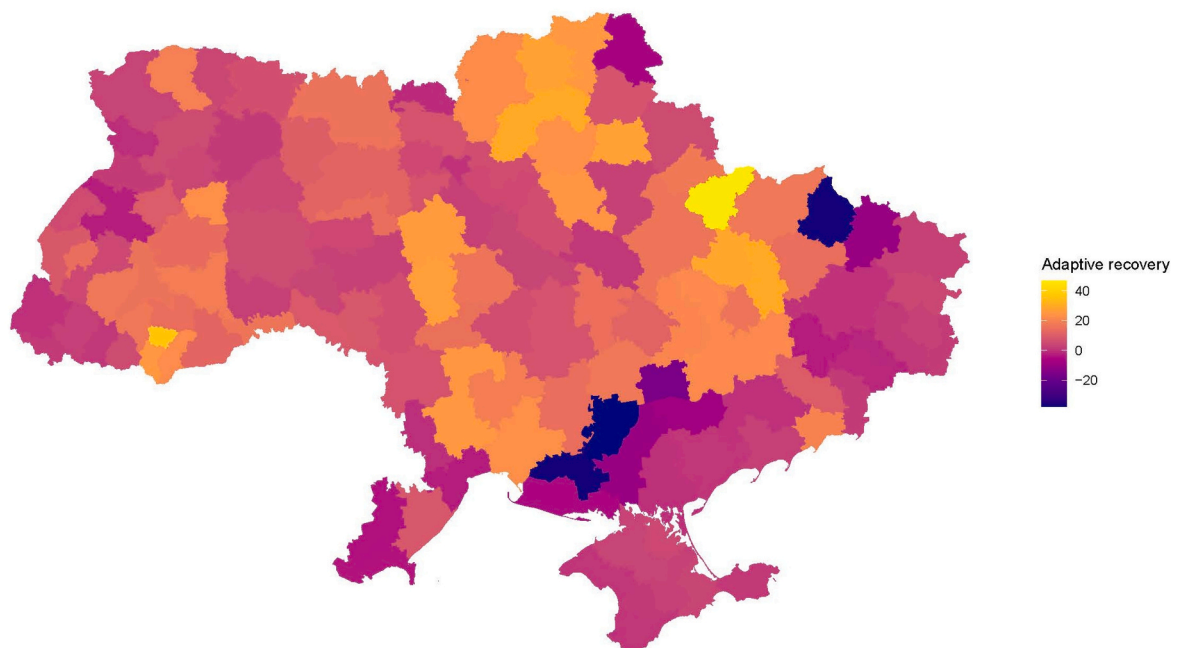


Fig. 4. Spatial variation in adaptive nighttime-light recovery, 2022–2024.

patterns of nighttime-light disruption across Ukrainian districts. Locations such as Kramatorskyi, Bakhmutskyi, and Pokrovskyi represent areas of particularly large declines in observed nighttime activity alongside intense military activity. At the same time, the variation in recovery scores indicates that some districts experienced stabilization or partial increases in nighttime-light intensity despite large initial shocks. These cross-sectional relationships remain descriptive, since strategically or economically important districts may also have been more likely to experience intense military activity.

However, nighttime light emissions during active conflict must be interpreted cautiously. In some cases, stable or increasing luminosity

may reflect war-related activity, such as fires, military operations, or emergency infrastructure deployment, rather than genuine economic recovery. Consequently, while nighttime lights provide valuable information on spatial patterns of observed activity during conflict, they should be interpreted alongside conflict data and other contextual indicators.

The relationship between conflict exposure and the nighttime-light indicators is consistent with the patterns observed in the nighttime light change analysis. Appendix Fig. A1 shows that districts experiencing higher levels of conflict generally display larger declines in nighttime luminosity between 2021 and 2022. Districts such as Kramatorskyi,

Table 5
Conflict severity and nighttime-light resistance and recovery.

Outcome	(1) Events	(2) Fatalities	(3) Events, adjusted	(4) Fatalities, adjusted
Composite indicator	−0.083*** (0.016)	−0.069*** (0.015)	−0.074* (0.032)	−0.053 (0.030)
Resistance indicator	−0.275* (0.125)	−0.137 (0.116)	0.097 (0.191)	0.029 (0.188)
Adaptive-recovery indicator	−1.157* (0.491)	−1.249** (0.449)	−2.140** (0.704)	−1.410* (0.626)
Pre-invasion NTL and log distance controls	No	No	Yes	Yes
Oblast fixed effects	No	No	Yes	Yes
Observations	139	139	137	137

Notes: Columns 1 and 3 measure conflict severity using the logarithm of recorded events during 2022–2024. Columns 2 and 4 use the logarithm of fatalities. Adjusted models include log nighttime-light intensity in 2021, log distance from conflict, and oblast fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses. Since the three outcomes are measured on different scales, coefficient magnitudes should not be compared directly across rows. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Bakhmutskiy, Pokrovskiy, and Kharkivskiy appear among the observations with both high numbers of violent events and some of the largest reductions in light emissions. These locations occupy the lower-right portion of the figure, indicating substantial contraction in observable nighttime activity following the escalation of hostilities.

The resistance and adaptive-recovery results reinforce this pattern. Many of the districts with the lowest composite nighttime-light scores correspond to areas that experienced intense military activity. For example, Kramatorskiy, Bakhmutskiy, Pokrovskiy, and Kupianskiy all appear among the lowest-ranked districts in the composite measure. These locations exhibit strongly negative resistance scores, reflecting severe initial declines in nighttime lights, combined with weak or limited recovery dynamics.

A second group of districts, including Okhtyrskiy, Bashtanskiy, and Chuhuivskiy, experienced large initial shocks but display somewhat stronger recovery scores. In these cases, nighttime light levels appear to have partially stabilized following the initial disruption. This suggests that observed nighttime activity recovered to some extent after the initial decline, although the indices do not identify the underlying economic or infrastructural mechanisms.

The results from both the nighttime light change analysis and the resistance–recovery framework point to a consistent pattern: districts exposed to more intense conflict tend to experience stronger declines in observed nighttime activity and weaker adaptive-recovery scores. At the same time, the considerable variation across districts highlights the spatial heterogeneity of wartime nighttime-light dynamics. Appendix Table A1 identifies seven districts in the top decile of conflict exposure whose nighttime-light declines were smaller than the national municipal average. None experienced stable or increasing luminosity. Moreover, excluding these districts increases the estimated post-2022 distance coefficient from 0.0498 to 0.0630, indicating that they do not drive the main spatial gradient.

Conclusions

The results provide several implications for the future spatial organization of economic activity in Ukraine. First, the strongly localized nature of nighttime light declines suggests that wartime disruption in observed nighttime activity is concentrated in close proximity to areas of intense conflict. This pattern indicates that the economic footprint of war is highly uneven across space and that future recovery and reconstruction are unlikely to follow a uniform trajectory. Instead, heavily affected districts may face more persistent challenges, including

damaged infrastructure, reduced productive capacity, and population losses, while locations farther from conflict zones may recover more rapidly and potentially attract economic activity.

The estimated spatial gradient is robust to alternative starting years and remains significant after the exclusion of highly conflict-exposed districts whose nighttime-light declines were smaller than the national average. In addition, the pre-period analysis finds no evidence that nighttime-light trends during 2018–2021 systematically differed with distance from later conflict locations. These checks strengthen confidence that the estimated gradient is not driven by the choice of sample period or a small number of unusual observations. Nevertheless, distance from conflict is not exogenously assigned, and the results should be interpreted as conditional spatial associations rather than causal effects.

Second, the substantial variation in nighttime-light resistance and adaptive recovery across districts points to the emergence of diverging local trajectories in observed nighttime activity. Districts that experienced severe initial declines and limited stabilization, such as Kramatorskiy, Bakhmutskiy, and Kupianskiy, are likely to require extensive and sustained reconstruction efforts before economic activity can return to pre-war levels. In contrast, districts with comparatively stable or improving nighttime-light trajectories may provide short-term support for wider economic adjustment. These areas could play a key role in supporting national recovery, particularly if they continue to attract displaced firms, labor, and investment.

Third, the observed spatial divergence in nighttime light intensity suggests that the war has significantly reshaped the spatial distribution of observed activity. The concentration of activity in less exposed areas may reflect both reductions in conflict-affected regions and the relocation of households, firms, and economic functions toward safer locations. If these dynamics persist, they may lead to a more polarized economic geography, with long-term implications for regional inequality, labor mobility, and infrastructure development. Without targeted policy interventions, such disparities risk becoming entrenched over time.

More broadly, these findings highlight the importance of spatially differentiated policy responses in the context of reconstruction and ongoing wartime adjustment. Policies aimed at rebuilding economic activity should account for the highly localized nature of wartime damage and the heterogeneity in local nighttime-light trajectories. In particular, heavily affected areas may require not only physical reconstruction but also targeted support to restore economic networks, attract population returns, and rebuild local institutions. At the same time, relatively less affected areas may benefit from policies that support sustainable growth and prevent excessive congestion or over-concentration of economic activity.

The analysis also demonstrates both the value and the limitations of satellite-based measures during active conflict. Nighttime lights provide consistent and timely spatial information where conventional statistics are unavailable, but they are not equivalent to local GDP, productive capacity, or welfare. Fires, military operations, and emergency infrastructure may contribute to observed luminosity, particularly in heavily exposed districts. For this reason, the results are best understood as evidence of uneven changes in observed nighttime activity and should be interpreted alongside conflict data and other contextual information.

The evidence suggests that the war is likely to leave a lasting imprint on Ukraine's economic geography. Understanding these spatial dynamics is therefore essential for designing effective reconstruction strategies and for promoting a more balanced and inclusive recovery process. Future research could strengthen this assessment by combining nighttime lights with firm-level activity, population mobility, infrastructure damage, electricity consumption, and other subnational indicators as these data become available.

CRediT authorship contribution statement

Alessandra Michelangeli: Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Umut Türk:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: *Uneven Resilience and Recovery During War: District-Level Evidence from Ukraine*. The authors confirm that all authors have read and approved

the final version of the manuscript and agree to its submission to *Research in Globalization*. The manuscript is the authors' original work, has not been published previously, and is not under consideration for publication elsewhere. All authors accept responsibility for the accuracy and integrity of the work. A separate Declaration of Interest file has been provided.

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Appendix A. Appendix

A.1. Conflict intensity and nighttime light decline

This appendix complements the analysis by examining whether the intensity of conflict events is associated with changes in nighttime light emissions, and by discussing the implications for interpreting luminosity as a proxy for economic activity in a war context.

Fig. A1 plots the change in nighttime light intensity between 2021 and 2022 against the logarithm of the number of recorded conflict events during 2022–2024 at the district level. A negative relationship emerges on average: districts experiencing a higher number of conflict events tend to exhibit larger reductions in nighttime lights. This pattern is consistent with the interpretation that intense military activity is associated with disruption to local economic systems and declines in observable nighttime activity. Districts such as Kramatorskyi, Bakhmutskyi, Pokrovskyi, and Kharkivskyi illustrate this pattern, combining high conflict intensity with substantial decreases in luminosity during the initial phase of the invasion.

However, the relationship is not uniform across locations. Seven districts in the top decile of conflict-event exposure experienced nighttime-light declines that were smaller than the national municipal average: Polohivskyi, Kupianskyi, Volnovaskyi, Beryslavskyi, Shostkynskyi, Donetskyyi, and Svativskyi (Appendix Table A1). None of these districts recorded a non-negative change in nighttime lights. They are therefore better described as having relatively moderate declines rather than stable luminosity. Together, these districts represent 5.0% of the sample but account for 33.7% of recorded conflict events and 18.6% of recorded fatalities during 2022–2024.

These patterns highlight an important measurement issue. During active conflict, nighttime light emissions may reflect multiple sources of illumination beyond civilian economic activity. In particular, fires, explosions, military operations, and emergency infrastructure can generate light that is detected by satellite sensors. As a result, observed nighttime luminosity in high-intensity conflict areas may partially capture conflict-related light emissions, thereby attenuating or masking declines in underlying economic activity.

This evidence suggests that the relationship between conflict intensity and nighttime lights should be interpreted with caution. While nighttime lights remain informative about broad spatial patterns of disruption, they may overstate economic activity in areas experiencing intense violence. The main analysis therefore focuses on distance-based measures of exposure, which are less directly affected by contemporaneous light emissions generated by conflict events themselves. As an additional sensitivity check, the continuous-distance model is re-estimated after excluding the seven high-conflict districts with relatively moderate nighttime-light declines. The post-2022 distance coefficient increases from 0.0498 to 0.0630 and remains statistically significant, indicating that these unusual observations do not drive the principal spatial gradient.

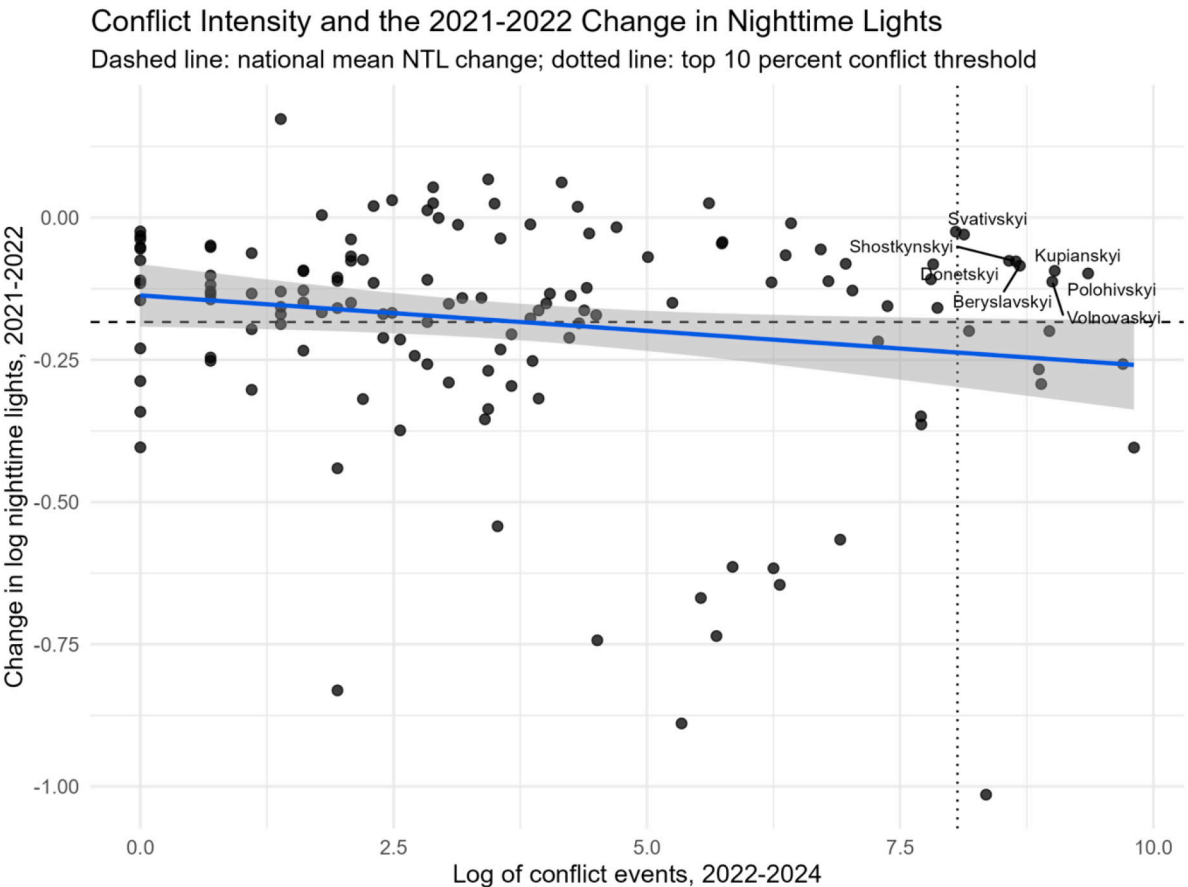


Fig. A1. Conflict intensity and the change in nighttime lights, 2021–2022.

Notes: The horizontal axis reports the logarithm of conflict events recorded during 2022–2024. The vertical axis reports the change in log nighttime-light intensity between 2021 and 2022. The solid line shows the fitted linear relationship, and the shaded area presents the 95% confidence interval. The horizontal dashed line indicates the national municipal average change in nighttime lights. The vertical dotted line marks the threshold for the top decile of conflict-event exposure. Labels identify highly exposed districts whose nighttime-light declines were smaller than the national municipal average.

Table A1
High-conflict districts with relatively moderate nighttime-light declines.

District	Region	Conflict events, 2022–2024	Fatalities, 2022–2024	Mean NTL, 2021	Change in log NTL, 2021–2022
Polohivskiy	Zaporizka	11,567	6718	0.116	–0.098
Kupianskyy	Kharkivska	8317	5567	0.123	–0.093
Volnovaskyy	Donetska	8120	6293	0.139	–0.113
Beryslavskyy	Khersonska	5894	2659	0.096	–0.084
Shostkynskyy	Sumska	5670	133	0.096	–0.077
Donetskyy	Donetska	5298	2339	1.383	–0.076
Svativskyy	Luhanska	3396	3653	0.060	–0.030

Notes: High-conflict districts are defined as those in the top decile of recorded conflict events during 2022–2024. The table includes districts whose decline in log nighttime lights between 2021 and 2022 was smaller than the national municipal average. None recorded a non-negative nighttime-light change. These seven districts account for 33.7% of recorded conflict events and 18.6% of recorded fatalities in the sample.

Table A2
Test for differential nighttime-light trends before the full-scale invasion.

	Log nighttime lights
Linear trend × log distance	0.0019 (0.0020)
District fixed effects	Yes
Year fixed effects	Yes
District -clustered standard errors	Yes
Observations	556

(continued on next page)

Table A2 (continued)

	Log nighttime lights
Districts	139
Within R^2	0.0025

Notes: The estimation period is 2018–2021. The linear trend equals zero in 2018 and increases by one in each subsequent year. Standard errors clustered by district district are reported in parentheses. The interaction is statistically insignificant ($p = 0.354$), providing no evidence that pre-2022 nighttime-light trends varied systematically with distance from later conflict locations.

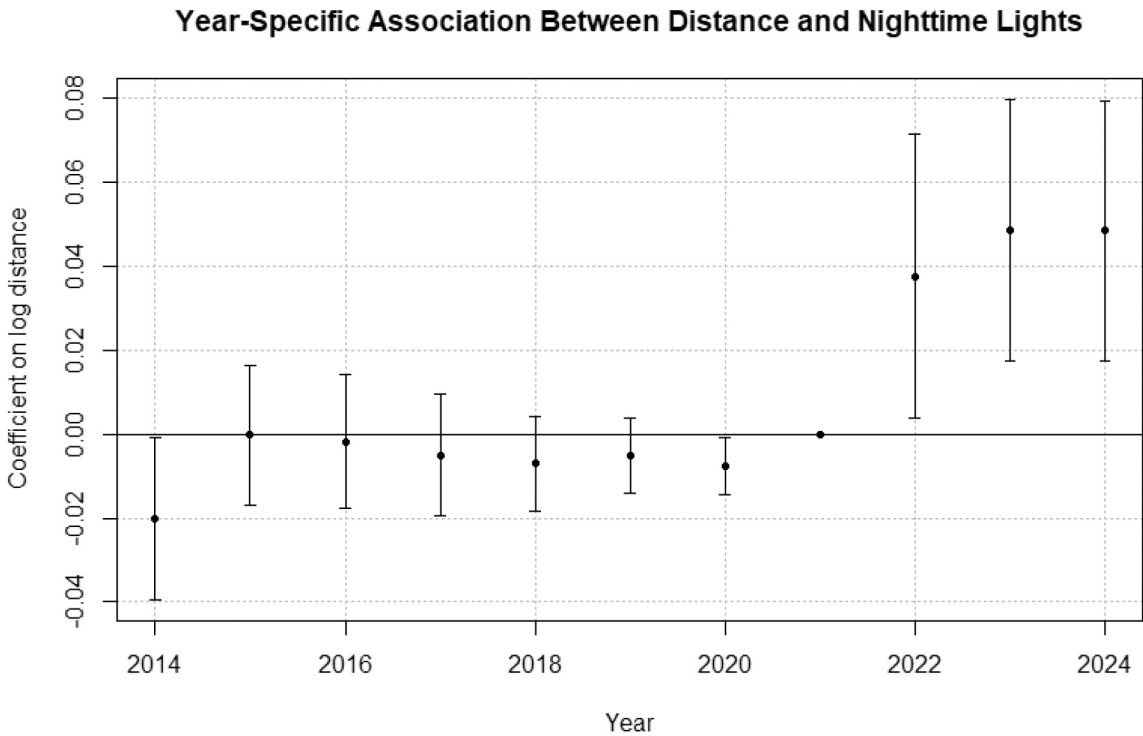


Fig. A2. Year-specific association between distance from conflict and nighttime-light intensity. **Notes:** Points report year-specific coefficients on log distance from a model including district and year fixed effects. The omitted reference year is 2021. Vertical bars show 95% confidence intervals calculated using district -clustered standard errors. The figure provides descriptive evidence on the timing of the distance gradient; it is not interpreted as a causal event-study design.

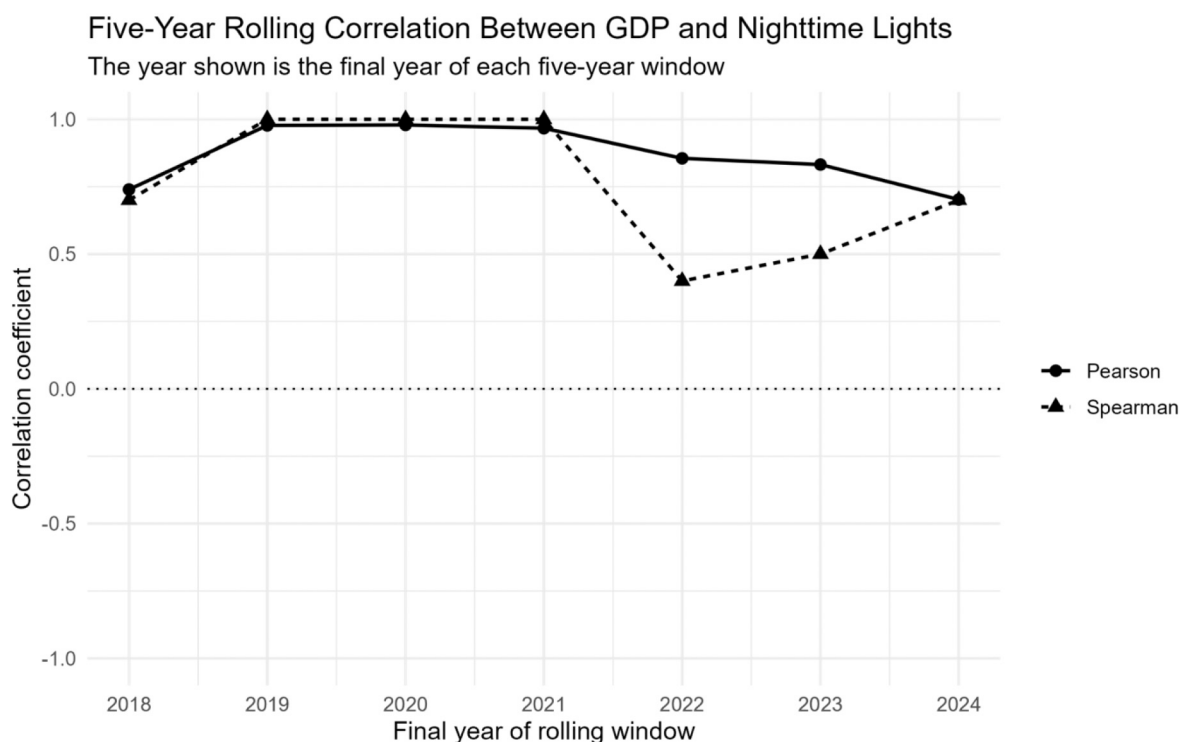


Fig. A3. Five-year rolling correlation between GDP and nighttime lights. **Notes:** The figure reports five-year rolling Pearson and Spearman correlations between national log GDP and aggregate log nighttime-light intensity. The year shown on the horizontal axis is the final year of each five-year window; for example, 2022 represents the 2018–2022 window. Correlations remain positive throughout the period but become less stable in windows that include the pandemic and the full-scale invasion.

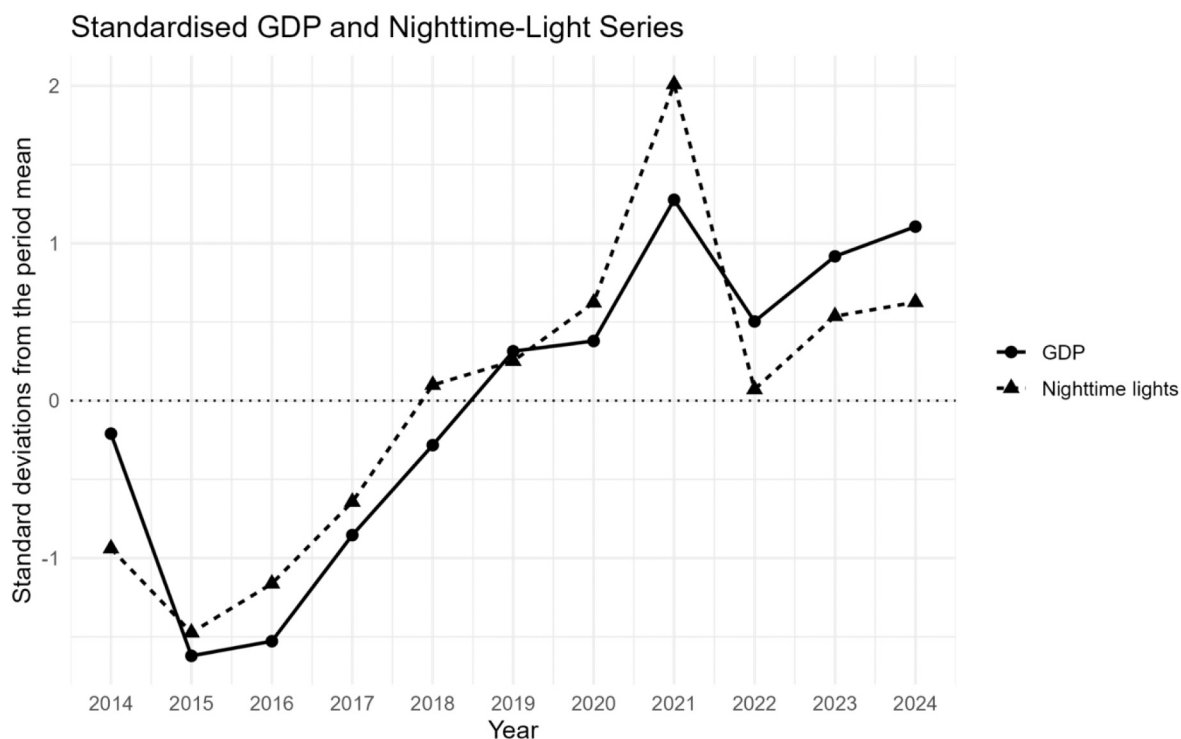


Fig. A4. Standardized GDP and nighttime-light series, 2014–2024. **Notes:** GDP and nighttime-light intensity are standardized over the full 2014–2024 period to have a mean of zero and a standard deviation of one. The figure compares their relative trajectories rather than their original units or annual growth rates. The two series broadly co-move through 2021 and both decline in 2022, but their subsequent recovery differs, with GDP rebounding more strongly than nighttime lights.

Table A3

Sensitivity to the starting year.

Sample	Coefficient	Clustered SE	p-value	Observations
2014–2024	0.0507	0.0165	0.0025	1529
2015–2024	0.0487	0.0163	0.0033	1390
2016–2024	0.0493	0.0161	0.0027	1251
2017–2024	0.0498	0.0160	0.0023	1112
2018–2024	0.0498	0.0158	0.0020	973
2019–2024	0.0491	0.0156	0.0020	834

Notes: Each model includes district and year fixed effects. The reported coefficient is the interaction between the post-2022 indicator and log distance. Standard errors are clustered by district.

Table A4

Sample-exclusion checks.

Sample	Post-2022 × log distance	p-value
Panel A: 2014–2024		
Full sample	0.0508	0.0025
Excluding Crimea	0.0531	<0.001
Excluding top 5% by conflict exposure	0.0466	0.028
Excluding top 10% by conflict exposure	0.0343	0.088
Excluding Crimea and top 10%	0.0471	0.007
Panel B: 2018–2024		
Full sample	0.0498	0.0020
Excluding seven high-conflict districts with moderate declines	0.0630	0.0007

Notes: All models include district and year fixed effects and use standard errors clustered by district. The seven districts in Panel B are listed in Appendix Table A1. Panel A and Panel B use different estimation periods and should not be compared as identical samples.

Table A5

Districts with the lowest composite nighttime-light scores.

District	Resistance index	Adaptive-recovery index	Composite index
Beryslavskiy	−6.54	−37.8	−2.06
Kupianskyi	−4.32	−36.7	−1.72
Khersonskiy	−2.25	−36.6	−1.45
Kramatorskyi	−13.0	0.49	−1.35
Pokrovskiy	−9.42	−3.11	−1.03
Nikopolskyi	−5.43	−15.9	−1.03
Bakhmutskiy	−10.5	0.67	−1.02
Siverskodonetskyi	−8.83	0.27	−0.81
Sumskiy	−8.88	5.18	−0.61
Okhtyrskiy	−12.65	17.70	−0.60

Table A6

Districts with the highest composite nighttime-light scores.

District	Resistance index	Adaptive-recovery index	Composite index
Bilohirskiy	1.03	2.44	0.569
Dzhankoislyi	0.341	4.65	0.568
Kurmanskyi	0.326	3.36	0.514
Feodosiyskyi	0.197	3.67	0.510
Perekopskyi	0.176	3.28	0.491
Luhanskyi	0.226	2.82	0.479
Mariupolskyi	−5.22	20.0	0.463
Simferopolskyi	0.259	1.62	0.435
Kerchenskyi	0.237	1.44	0.425

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