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SPATIOTEMPORAL CHANGES IN THE CONGESTION INDEX OF STREETS AND ROADS IN THE ARMED CONFLICT CONDITIONS

Summary. *This article examines the impact of war on the formation of urban transport flows. During armed conflicts, the transport infrastructure of cities undergoes significant changes, which greatly affects the mobility and safety of the population. The need to study this issue is particularly relevant in the context of the ongoing Russian-Ukrainian war, which has caused the largest migration in Europe since World War II. The paper explores the dynamics of these changes and ways to adapt urban transportation systems to war conditions. The study aims to determine the parameters of urban transport zones with specific disruptions in network link congestion indices during different phases of the full-scale invasion of Ukraine by the Russian Federation. The research methodology is based on analyzing statistical data on population movements, applying traffic flow models, and conducting a systematic analysis of the interaction between various components of urban transport systems. The goal of this study is to establish the relationships between the areas of cities where disruptions in congestion indices were observed during the initial phase of the invasion. The cities studied are Lviv and Kyiv, whose road networks are also described in the article. Polynomial regression models with two independent variables (the congestion index and the number of days from the beginning of each phase) were developed for three predefined time phases, each with distinct features of the armed conflict. The dependent variable is the area of the city experiencing disruptions in the congestion index relative to normal traffic flow conditions. The study concludes that the relationship between changes in the congestion index and the area of the city experiencing deviations is directly proportional. The absolute values of the indicators studied are lower for Lviv's network than for Kyiv's.*

Key words: *travel time, transport system, road network, congestion index, regression analysis, accessibility of transport zones, transport modeling.*

1. INTRODUCTION

Throughout history, humanity has been continuously affected by various natural and man-made disasters. These emergencies have a significant impact on the environment, sometimes altering it drastically. It is crucial for scientists to study these events to understand better the mechanisms through which they affect various aspects of life. Analyzing changes in traffic patterns during disasters helps in

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understanding these impacts and also aids in developing preventive and emergency measures to mitigate or avoid disruptions in transportation systems.

Although considerable research has been conducted on the impact of natural disasters on transportation systems, the field continues to evolve. New methods provide deeper insights into these changes, especially in areas that were previously difficult to study, such as the impact of armed conflict on transportation behavior.

The full-scale invasion of Ukraine by the Russian Federation on February 24, 2022, marked the largest humanitarian conflict in Europe since World War II. The military actions triggered a humanitarian crisis, forcing millions to flee in search of safer living conditions, resulting in mass population displacement. This emergency migration led to significant disruptions in the functioning of transportation systems, while the destruction of infrastructure due to military actions created additional challenges.

The rarity of events such as war, combined with the difficulty of obtaining initial data for analysis, has led to a shortage of quality research on the formation of transportation flows during humanitarian conflicts. Understanding transportation systems` functioning and the potential disruptions they face under such conditions is critical for ensuring the population's safety and timely humanitarian and military aid delivery.

2. LITERATURE REVIEW

Analysis of research on the impact of emergencies on transportation systems has demonstrated significant interest among scholars. A prominent example in the transportation literature is the recent COVID-19 pandemic. Other disasters, such as earthquakes, terrorist attacks, and floods, are typically evaluated based on their effects on networks observed after events.

In the study [1], researchers analyzed the primary evacuation routes for residents following the Kumamoto earthquake and found that the average travel time increased by 2.56 times. However, this trend was observed only during the day; at night, travel times were close to normal. This increase was attributed to both heightened demand and the closure of some routes due to destruction or for specialized vehicles use only.

Probabilistic modeling was applied to the city of Messina (Sicily, Italy) for the historical event of 1908 and for a set of simulated earthquakes that correspond to Italy's national probabilistic seismic hazard model. The study revealed that the average travel duration increased by 70–90 % compared to baseline values, while the average travel distance rose less significantly – by only 15–20 %.

Similar to earthquakes, floods can have both a direct impact on road infrastructure – through destruction and inundation – and an indirect impact, such as altering usual traffic patterns and disrupting business operations. Some studies indicate that one of the leading causes of fatalities in cities during floods is the presence and movement of vehicles on flooded roads [3, 4].

In the study [5], the authors found that travel duration during a flood increases on average by 27 % compared to normal conditions. This increase is not excessively high, as some vehicles may travel faster than usual due to reduced traffic volume. This results from a significant number of users opting not to travel during an emergency.

One of the recent and unique emergencies is the COVID-19 pandemic. Its impact on the transportation systems of various cities has been extensively studied. The measures implemented to prevent the spread of the virus were quite strict, though they varied across different cities and countries. Social distancing, curfews, restrictions, and even complete cancellations of public transportation, along with prohibitions on traveling beyond a certain distance from one’s residence, significantly affected the transportation behavior of the population [6, 7]. Analysis of travel times by the TomTom service further confirms a substantial reduction in traffic volumes in many cities worldwide, including two Ukrainian cities: Kyiv (with an overall decrease of 51 %) and Odesa (44 %) [8].

One extraordinary event that can be fully characterized as a humanitarian conflict and is inherently unpredictable is a terrorist attack. One of the most significant and well-known examples is the terrorist act in New York on September 11, 2001. Research indicates a sustained decrease in demand for air travel in the United States until November 2003, with an overall reduction of 7.4 %, while the immediate decline was 26.5 % [9].

As a result, many Americans chose to travel by private car instead of air transportation for domestic trips. This shift led to increased traffic volume and a rise in road traffic accidents [10]. In the year following the attack, approximately 1,600 more people died in traffic accidents in the U.S. than in the previous year. The average monthly increase in mileage per resident after September 2001 was 27.2 miles, compared to an earlier average increase of 9.9 miles. Moreover, similar changes were observed not only in the immediate vicinity of the events but across most states, regardless of their geographical location, although these changes were uneven [11].

Despite the widespread interest in studying changes in transportation systems resulting from emergencies, the impact of armed conflicts, such as war, remains insufficiently explored.

Our previous research is the first modern study on this topic. It was published in 2023 [12]. It focused on the transportation systems of six Ukrainian cities (Kyiv, Kharkiv, Odesa, Dnipro, Lviv, Mariupol) with varying characteristics of location and roles in the full-scale war and on the Ukrainian road network. A database of crucial wartime events was created for each city. Transportation modeling was conducted using a new rapid planning tool, Rapidex [13]. The coefficient of variation was employed as a metric for travel time for each link of all studied networks, including the intercity road network of Ukraine. It was found that larger variability was observed in the peripheral areas of the cities. The highest variability in travel time occurred in Kyiv, Kharkiv, and Mariupol – cities that experienced occupation attempts. The events of the invasion led to an increase in traffic congestion levels by 50 % in Kyiv, 55 % in Kharkiv, and 30 % in Mariupol. Demand formation increased by 200 %, 150 %, and 300 %, respectively.

In addition to transportation modeling, a sociological survey was conducted [14]. The study of transportation behavior among the population of Ukraine at the initial stage of the full-scale invasion revealed that 83.8 % of residents evacuated from their permanent places of residence within a month of the full-scale war's onset, with 50.8 % evacuating within the first week. The largest share of respondents (30.0 %) evacuated to cities in the western regions of Ukraine, while 24 % left the country.

3. RESEARCH STATEMENT

The study [12] identified the main behavior patterns among road users in the context of armed conflict during the initial stage of the full-scale war in Ukraine. However, as this research is relatively new and unique in its focus on such events, there remains ample opportunity to explore even deeper scientific questions.

It is essential to thoroughly assess the current state of transportation systems under emergency conditions and to understand all possible changes and their underlying causes to formulate recommendations. Although modern society often avoids discussing the possibility of invasions due to the topic's sensitivity, this risk is always present in any country.

The aim of this study is to determine the dependencies between the areas of city districts where disruptions in the congestion index of network links are observed during the initial phase of the full-scale invasion. The following tasks have been defined to achieve this goal:

- conduct a statistical analysis of changes in the congestion index of network links over the study period.
- form matrices to represent the dependencies between the areas with disruptions from the congestion index and the number of days since the beginning of the defined phase.
- build mathematical models for the obtained matrices, determining the optimal type of curve that describes the disruptions.

4. CHARACTERISTICS OF RESEARCH OBJECTS

During the war, each city operates under different conditions, influenced by factors such as geographical location, the level of development of urban infrastructure, transportation connections, and more. For this study, two cities were selected – Kyiv and Lviv. The road networks of these cities were obtained from the OpenStreetMaps mapping service using the Rapidex tool and are depicted in Fig. 1.

Kyiv Lviv

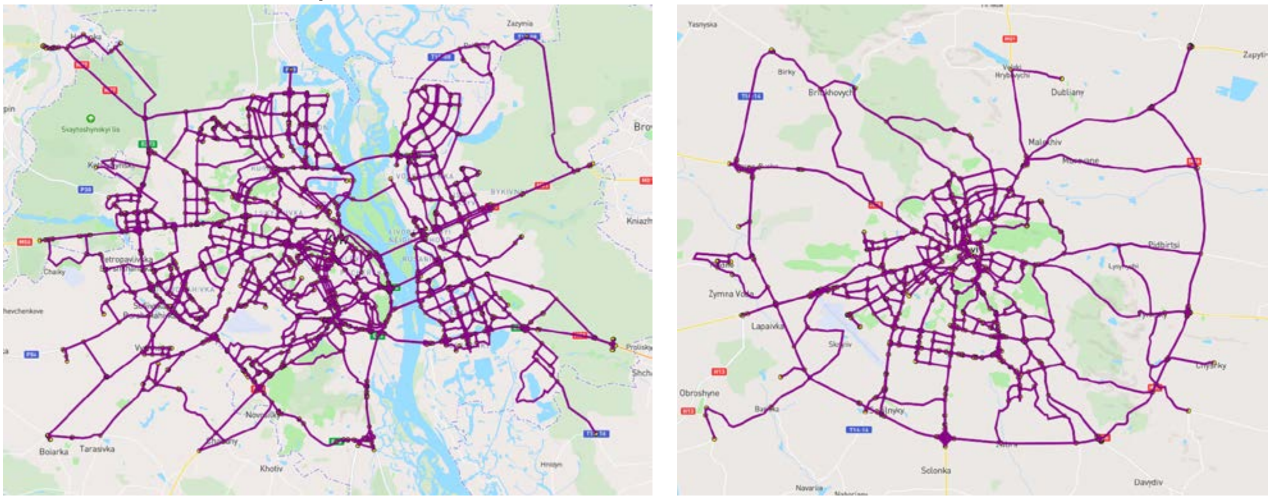


Fig. 1. The road networks of the studied cities.

As the capital, Kyiv was the Russian Federation's primary target. However, only the suburban towns to the northeast of Kyiv fell under occupation, making evacuation from those areas nearly impossible. In response to the threat, many Kyiv residents attempted to leave from the first day of the invasion.

A distinctive feature of the city is the Dnipro River, which divides it into two parts, making bridges crucial to the functioning of Kyiv's road network. With the onset of the full-scale invasion, these bridges were (partially) closed to private vehicle traffic.

Kyiv's road network configuration can be described as radial-ring; however, the ring roads and streets are not clearly defined and, due to geographical features, are not fully closed. Additionally, some areas have hexagonal layouts (e.g., Obolon) and rectangular grids (e.g., Podil and the city's left bank).

Lviv is located in western Ukraine and has direct rail connections with Poland. With the onset of the full-scale war, it became a major logistical and humanitarian hub. Millions of people from across the country arrived in the city, either staying there or continuing their journeys to smaller settlements or abroad. Additionally, much of the humanitarian aid from European countries arrived in Lviv before being distributed to other locations.

Lviv's road network also follows a radial-ring configuration, with elements of freeform and rectangular layouts in the city center. However, the smaller ring roads are (partially) incomplete due to geographical features, and the city's bypass ring road has a missing link in the north. It negatively affects traffic flow, as transit vehicles from the European E40 highway often have to enter the city to avoid lengthy detours.

5. MAIN PART

The initial data for the analysis consisted of travel times along the links of the road networks of the specified cities, obtained using the Rapidex tool for the period from February 26, 2022, to May 15, 2022. The primary calculated indicator is the congestion index of the links, which is defined as follows [15]:

$$CI_i = \frac{TT_i}{FFTT_i}, \tag{1}$$

where CI_i – link congestion index i; TT_i – observed travel time, sec.; $FFTT_i$ – free-flow travel time, sec.

For both cities, spatial-temporal disruptions in traffic indicators and road networks have been identified. Disruption is defined as a specific (atypical) state of the indicator that significantly diverges from the overall range of values.

To determine these disruptions, data filtering was conducted on the average congestion index of departure and destination zones and the vehicle kilometers traveled within the zones to isolate recurring trends. The next step involved a spatial-temporal analysis to identify areas with the largest disruptions in each city. The obtained indicators of the road networks included the area of the city affected by the disruptions, changes in accessibility and traffic flow, and the impact on capacity.

Based on these steps, three phases of population migration in Ukraine were identified:

– Phase 1: February 26, 2022 – March 14, 2022. This phase describes the beginning of the full-scale invasion, the evacuation of residents due to the very fact of the large war, and the approaching occupation.
– Phase 2: March 28, 2022 – April 11, 2022. This period is characterized by migration related to the de-occupation of northern regions of Ukraine.
– Phase 3: April 26, 2022 – May 15, 2022. Approximately one month after the de-occupation of the northern regions, another phase of migration is observed, indicating the population's adaptation to danger and a desire to return to their original places of residence.

For each of the described periods, the main statistical indicators of the congestion index for both cities have been determined and recorded in Table 1. The upper limit of the congestion index range for further processing was defined using the 'three sigma' rule, which is the sum of the mathematical expectation and three times the average standard deviation [16].

Table 1

Main statistical characteristics of the congestion index

Period	Statistical characteristic	Kyiv	Lviv
Phase 1	Mathematical expectation, μ	1.01	0.78
	Variance, D	0.28	0.06
	Standard deviation, σ	0.53	0.25
	$\mu + 3 \cdot \sigma$	2.6	1.53
Phase 2	Mathematical expectation, μ	1.10	1.04
	Variance, D	0.40	0.39
	Standard deviation, σ	1.01	0.78
	$\mu + 3 \cdot \sigma$	3.0	2.9
Phase 3	Mathematical expectation, μ	1.48	1.17
	Variance, D	0.84	0.58
	Standard deviation, σ	0.91	0.76
	$\mu + 3 \cdot \sigma$	4.23	3.45

Next, for each phase and city, matrices of the areas of zones (*Ar*) with disruptions were created, featuring two predictors: the congestion index (*CI*) and the number of days since the beginning of the defined phase (*d*). An example of such a matrix is presented in Table 2.

Table 2

An example of a matrix showing the area of zones with disruptions in relation to the congestion index level and the number of days since the beginning of the phase

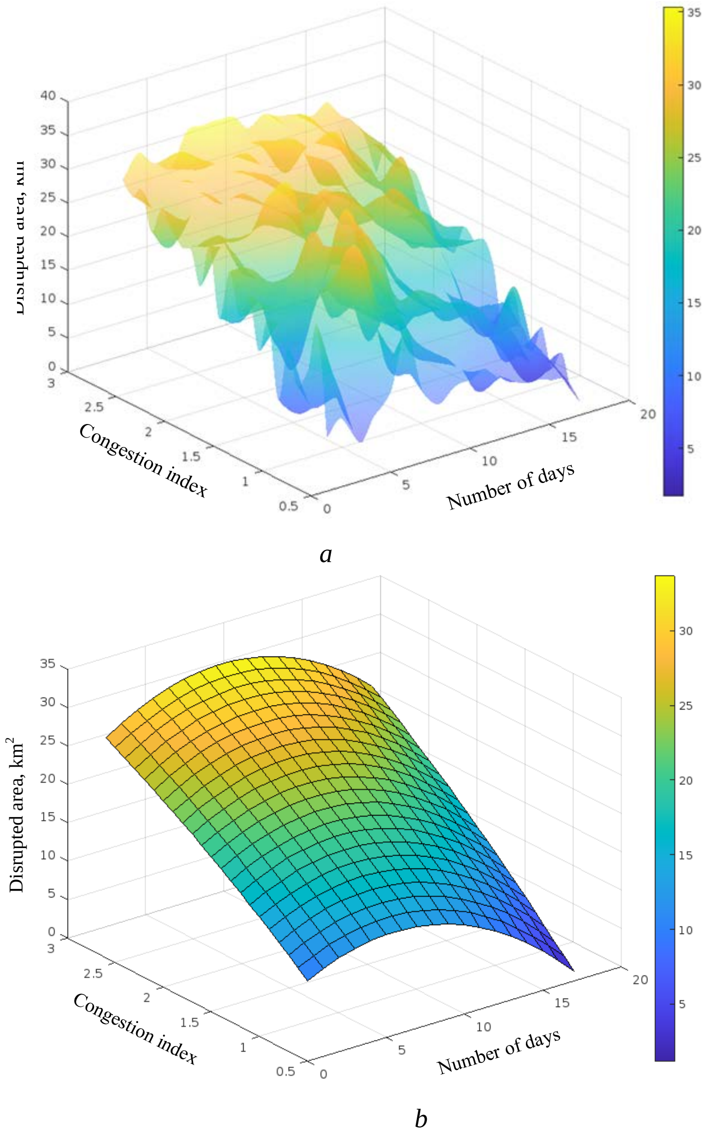
The number of days since the beginning of the phase	Congestion index				
	0.5	0.6	0.7	…	m
1	$Ar_{0.5,1}$	$Ar_{0.6,1}$	$Ar_{0.7,1}$	…	$Ar_{m,1}$
2	$Ar_{0.5,2}$	$Ar_{0.6,2}$	$Ar_{0.7,2}$	…	$Ar_{m,2}$
3	$Ar_{0.5,3}$	$Ar_{0.6,3}$	$Ar_{0.7,3}$	…	$Ar_{m,3}$
…	…	…	…	…	…
n	$Ar_{0.5,n}$	$Ar_{0.6,n}$	$Ar_{0.7,n}$	…	$Ar_{m,n}$

The specified indicators have the following conditions:

$$0.5 \le CI \le m,$$
$$m = \mu + 3 \cdot \sigma, \qquad (2)$$
$$1 \le d \le n,$$

where *CI* – congestion index; *m* – the sum of the mathematical expectation and three times the average standard deviation; μ – mathematical expectation; σ – standard deviation; *n* – the number of days in the phase.

Polynomial models of the second order were constructed for all obtained matrices (Equations (3)–(8)). The initial data were also graphically represented (Figs. 2, *a*–7, *a*), along with the 3D graphs of the obtained models (Figs. 2, *b*–7, *b*).



a

b

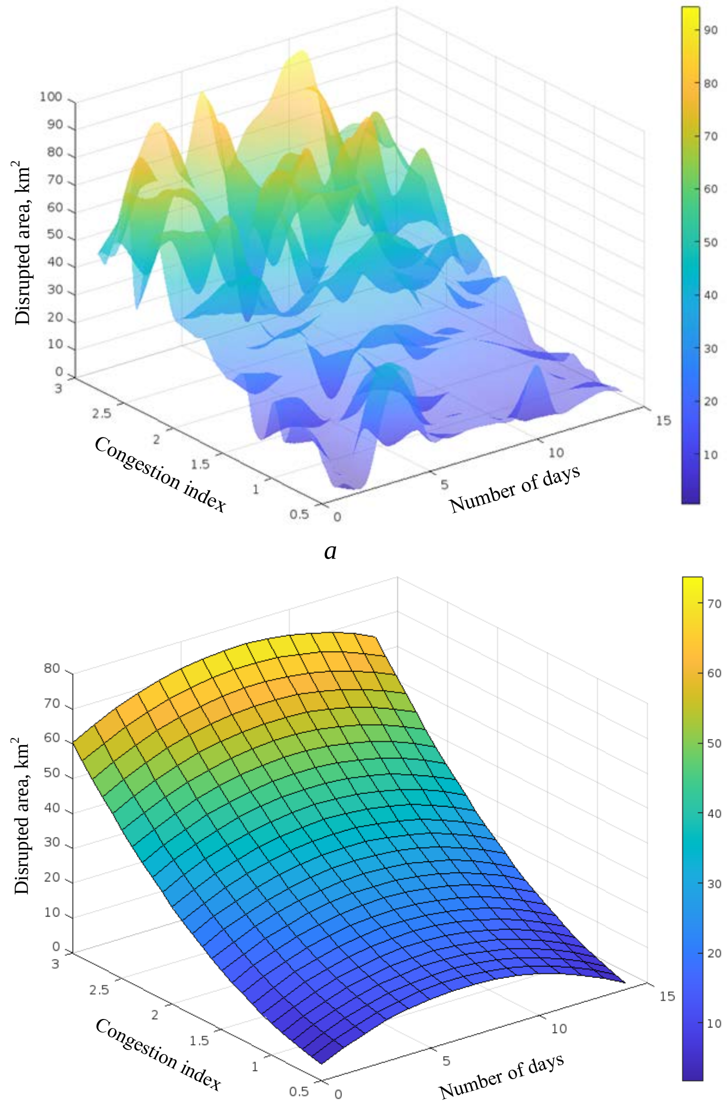
Fig. 2. Experimental dependence (a) and model of the dependence (b) between the congestion index, phase duration, and the area of zones with disruptions for Phase 1 of the city of Kyiv

The dependency model for this phase describes a directly proportional change in the disrupted area as the congestion index increases. The change in the number of days from the start of the phase is initially directly proportional, but after six days, it becomes inversely proportional. The maximum disrupted area is observed six days after the start of the phase, with an increase of 17 % at a congestion index of 0.5. For the maximum congestion index (2.6), the disrupted area grows up to seven days into the phase (by 13 %), but after 13 days, the disrupted area falls below the initial level.

Model of dependence for Phase 1 in the city of Kyiv:

$$F(Ar)_{Kyiv,1} = 11.5704 \cdot CI - 0.9314 \cdot CI^2 + 0.9778 \cdot d - 0.094 \cdot d^2 + 0.1553 \cdot CI \cdot d + 4.8692,$$
$$R^2 = 0.8268. \quad (3)$$

In the depicted experimental dependency (Fig. 2, *a*), significant spikes in disrupted area are observed between the 5th and 8th day of the phase for a congestion index between 0.9 and 1.3. Closer to the end of the phase, with a congestion index ranging from 0.5 to 1.3, the disrupted area reaches lower values.



b

Fig. 3. Experimental dependence (a) and model of the dependence (b) between the congestion index, phase duration, and the area of zones with disruptions for Phase 2 of the city of Kyiv

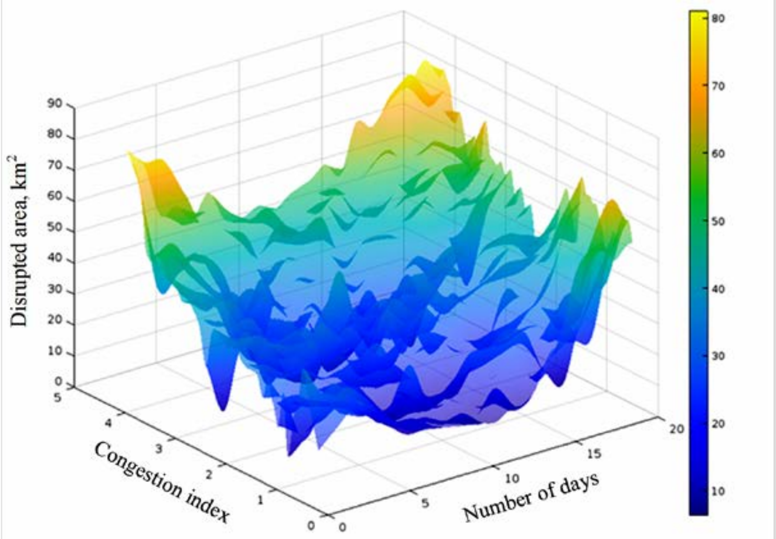
Model of dependence for Phase 2 in the city of Kyiv:

$$F(Ar)_{Kyiv,2} = -1.5239 \cdot CI + 6.7978 \cdot CI^2 + 2.9024 \cdot d - 0.2295 \cdot d^2 + 0.204 \cdot CI \cdot d + 3.7672,$$
$$R^2 = 0.7703. \quad (4)$$

The dependency in Fig. 3, *a* shows a significant spike in the disrupted area for a congestion index of 0.5 and a phase duration of 3 to 4 days. Other notable disruptions occur as the congestion index rises above 2.

For the model of Phase 2 in Kyiv, a direct relationship between the disrupted area and the congestion index is also observed. The increase for congestion index values between 0.5 and 1.1 is relatively smooth, with a more rapid change beyond that point. Towards the middle of the phase, the disrupted area increases, gradually decreasing afterwards.

a



b

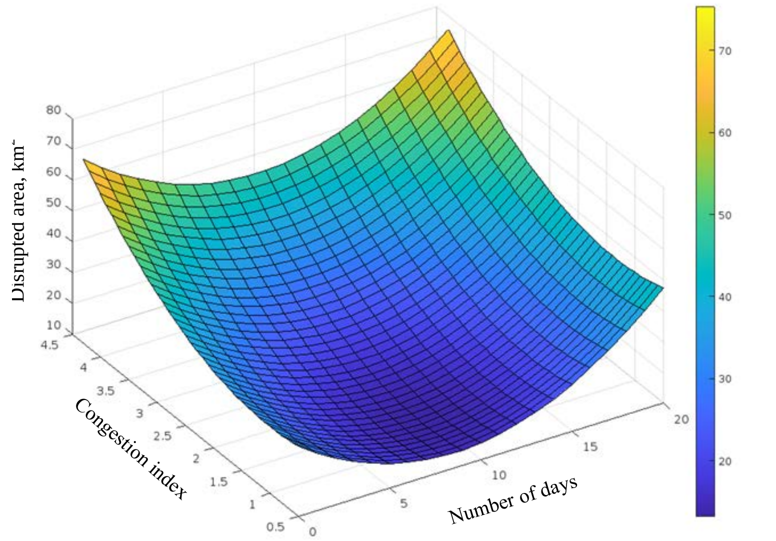


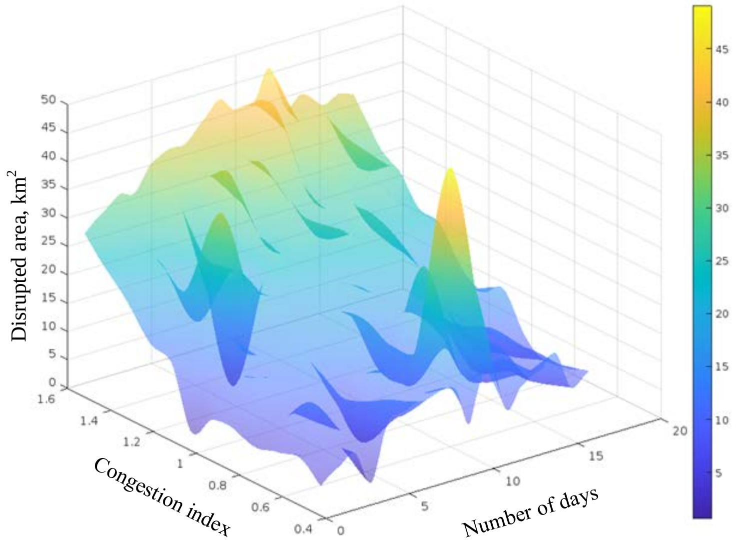
Fig. 4. Experimental dependence (a) and model of the dependence (b) between the congestion index, phase duration, and the area of zones with disruptions for Phase 3 of the city of Kyiv

Model of dependence for Phase 3 in the city of Kyiv:

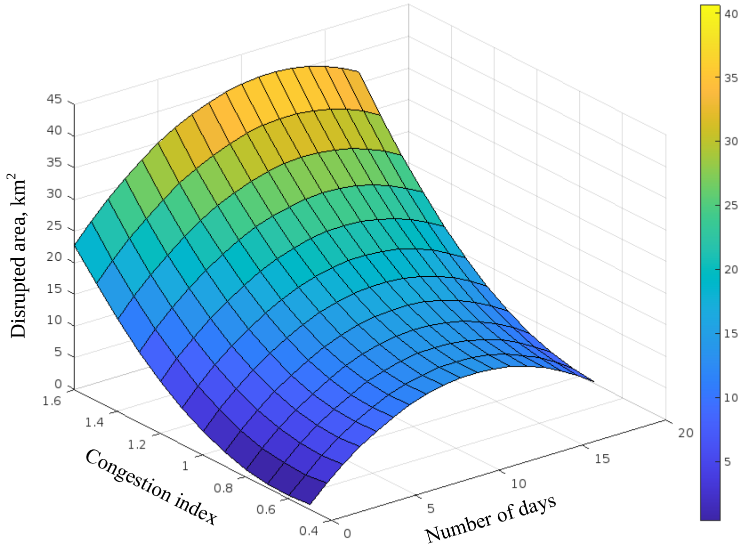
$$F(Ar)_{Kyiv,3} = -7.368 \cdot CI + 3.565 \cdot CI^2 - 4.1285 \cdot d + 0.2465 d^2 - 0.1202 \cdot CI \cdot d + 35.4445, \quad R^2 = 0.7979. \tag{5}$$

The experimental data for Phase 3 in Kyiv do not exhibit a significant number of outliers, except for a sharp decrease in the disrupted area for one day with a congestion index of 1.1 and two days with a congestion index of 2.7.

Phase 3 in Kyiv shows an apparent reduction in the disrupted area depending on the number of days, decreasing until nine days, after which it sharply increases. This reduction reaches up to 50 % of the initial value, and after 17 days, there is an increase of 15–60 %, depending on the congestion index. A notable feature of the dependence of the disrupted area on the congestion index is that at first (with congestion index values of 0.5–1), the relationship is inversely proportional, but later it becomes directly proportional.



a



b

Fig. 5. Experimental dependence (a) and model of the dependence (b) between the congestion index, phase duration, and the area of zones with disruptions for Phase 1 of the city of Lviv

Model of dependence for Phase 1 in the city of Lviv:

$$F(Ar)_{Lviv,1} = -30.0194 \cdot CI + 23.833 \cdot CI^2 + 2.4031 \cdot d - 0.1334 \cdot d^2 + 0.4275 \cdot CI \cdot d + 9.8481, \quad R^2 = 0.8184. \tag{6}$$

The change in this experimental dependence is quite smooth, with notable outliers observed: one for a congestion index of 0.6 at 11 days of the phase and another for 1.2 at four days. An additional outlier with a low value is noted for a congestion index of 0.7 at six days of the phase.

In Lviv, during Phase 1, the change in the disrupted area initially occurs in a directly proportional manner concerning the number of days. However, after approximately ten days, it shifts to an inversely proportional relationship. There is a direct dependence between the disrupted area and the congestion index. For days 1–8, a slight decrease (up to 10 %) in the disrupted area is observed for congestion indices of 0.5–0.7, followed by a sharp increase in value.

Model of dependence for Phase 2 in the city of Lviv:

$$F(Ar)_{Lviv,2} = 8,6562 \cdot CI + 1,3285 \cdot CI^2 + 3,3721 \cdot d - 0,2312 \cdot d^2 + 0,1926 \cdot CI \cdot d - 7,2994,$$
$$R^2 = 0,8362. \tag{7}$$

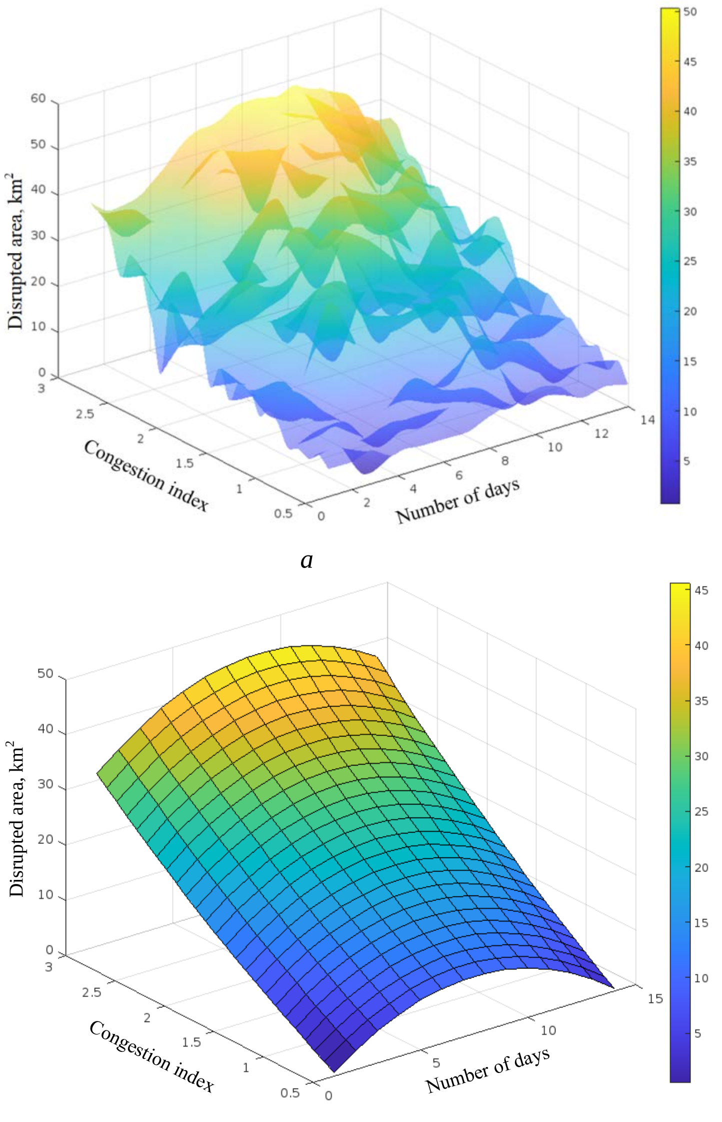


Fig. 6. Experimental dependence (a) and model of the dependence between (b) the congestion index, phase duration, and the area of zones with disruptions for Phase 2 of the city of Lviv

In the experimental data for Phase 2 in Lviv (Fig. 6, *a*), a clear outlier is the low value of the disrupted area for a congestion index of 2.2 on the first day of the phase. Generally, the values of the disrupted area are higher in the middle of the phase and somewhat lower at the beginning and end.

In this model, the disrupted area almost linearly increases with the growth of the congestion index. At the same time, the dependence on the number of days is directly proportional until the middle of the phase and then becomes inversely proportional. The relationship between the change in the disrupted area and the congestion index is close to linear.

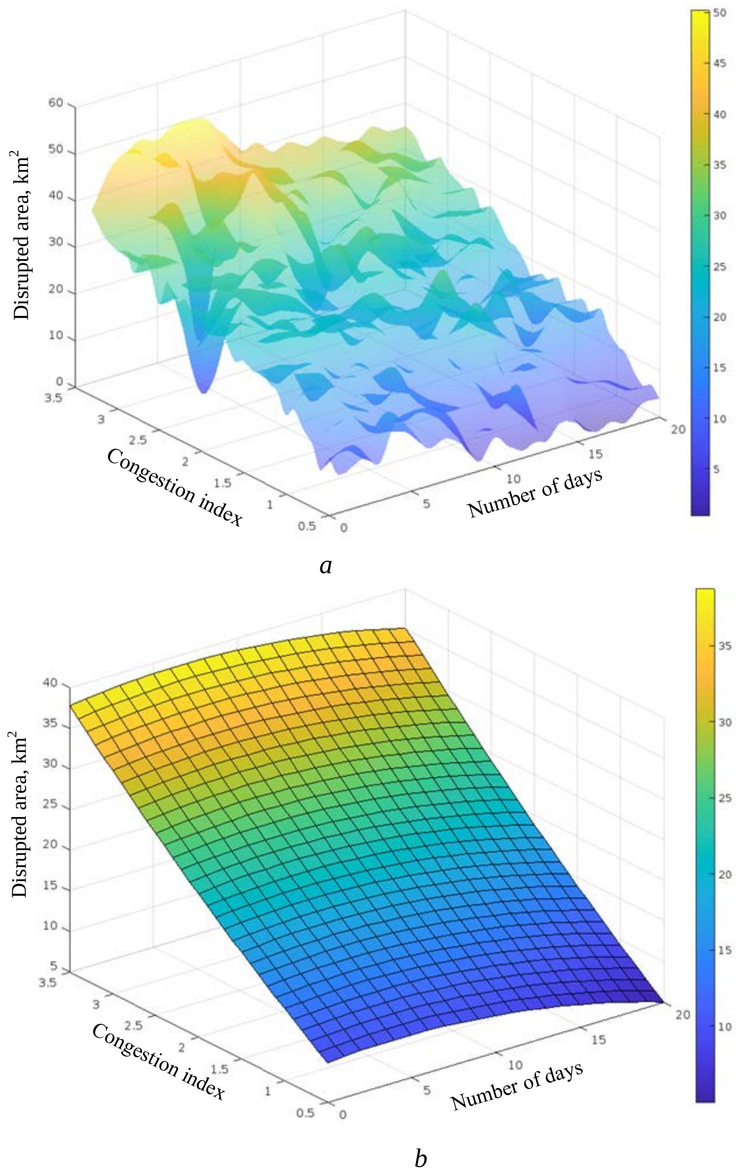


Fig. 7. Experimental dependence (a) and model of the dependence between (b) the congestion index, phase duration, and the area of zones with disruptions for Phase 3 of the city of Lviv

Model of dependence for Phase 3 in the city of Lviv:

$$F(Ar)_{Lviv,3} = 7.2056 \cdot CI + 0.5316 \cdot CI^2 + 0.1548 \cdot d - 0.0207 \cdot d^2 + 0.0347 \cdot CI \cdot d + 6.1169, \quad R^2 = 0.8335. \tag{8}$$

According to this experimental dependency, the disrupted area is higher during the first ten days of the phase and for a congestion index greater than 2.5. An outlier with a low value is observed for a congestion index of 2.4 at two days.

The dependence model for Phase 3 in Lviv does not exhibit a precise parabolic shape; instead, it is closer to linear. The disrupted area is directly proportional to the congestion index, with a slight initial increase (up to 2 % above the initial value) as the number of days in the phase increases. However, after approximately ten days, the relationship becomes inversely proportional, resulting in a decrease of up to 50 % at a congestion index of 0.5, up to 20 % at an index of 2.0, and up to 8 % at an index of 3.5.

The values of the congestion index and the disrupted area are lower for Lviv than for Kyiv, which can likely be attributed to the differences in the sizes of the cities and the specific characteristics of the wartime events that occurred in each.

6. CONCLUSIONS AND RESEARCH PERSPECTIVES

The result of this study is the development of mathematical models that describe the relationship between the disrupted area, the congestion index of links, and the number of days since the beginning of the full-scale invasion phase for Lviv and Kyiv. A clear direct proportional relationship is observed between the congestion index and the disrupted area.

The findings can be utilized to understand the characteristics of traffic flow formation during the initial phases of humanitarian conflicts, assess the potential temporal and spatial aspects of migration (evacuation) among city residents, and develop traffic management schemes based on military events.

In the long term, the models developed in previous research can be used to analyze changes in demand and determine the losses in the capacity of transportation networks. This will help identify priorities for which links require reconstruction, thereby enhancing the efficiency of the recovery process. Moreover, the results obtained will provide a foundation for formulating fundamental principles that increase the resilience of urban transportation systems, particularly in the context of armed conflicts. By studying the factors that contribute to the resilience of these systems, we can develop strategies that ensure transportation networks remain functional, adaptive, and capable of quickly recovering after disruptions.

Such understanding is crucial for minimizing the negative impact on civilian life and ensuring access to essential services during crises.

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ПРОСТОРОВО-ЧАСОВІ ЗМІНИ ІНДЕКСУ ЗАВАНТАЖЕННЯ ВУЛИЦЬ ТА ДОРІГ В УМОВАХ ЗБРОЙНОГО КОНФЛІКТУ

Анотація. *У статті досліджено вплив війни на формування транспортних потоків у містах. В умовах гуманітарних конфліктів транспортна інфраструктура міст зазнає серйозних змін, що істотно впливає на мобільність та безпеку населення. Особливо актуальна необхідність вивчення цього питання у контексті сучасної російсько-української війни, що спричинила наймасовішу міграцію населення у Європі з часів Другої світової війни. У роботі вивчено динаміку змін та способи адаптації системи міського транспорту до умов війни. Дослідження полягає у визначенні параметрів транспортних зон міст із особливими відхиленнями індексу завантаження відрізків мережі протягом кількох фаз повномасштабного вторгнення російської федерації (РФ) в Україну. Методологія дослідження ґрунтується на аналізі статистичних даних про пересування населення, використанні моделей транспортних потоків та системного аналізу взаємодії різних складових системи міського транспорту. Мета цього дослідження – визначення залежності між площею міста, де спостерігаються відхилення у показниках індексу завантаження відрізків вулично-дорожньої мережі протягом початкової фази повномасштабного вторгнення. Досліджено міста Львів та Київ, характеристику вулично-дорожніх мереж яких також наведено у статті. Для попередньо визначених трьох часових фаз, із різними особливостями перебігу збройного конфлікту, побудовано моделі поліноміальної регресії із двома незалежними змінними (індекс завантаження та кількість днів від початку фази). Залежною змінною є площа території міста з відхиленнями індексу завантаження від нормального стану транспортних потоків. Визначено, що залежність між зміною індексу завантаження та площею із відхиленнями є прямо пропорційною. Абсолютні значення досліджуваних показників нижчі для мережі Львова, ніж для Києва.*

Ключові слова: *тривалість пересування, транспортна система, вулично-дорожня мережа, індекс завантаження, регресійний аналіз, доступність транспортних зон, транспортне моделювання.*