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Economic growth of countries in the context of military operations

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Purpose. The purpose of the study is to assess the economic growth of Ukraine, Syria, and Palestine under wartime conditions, compare growth models (Solow, MRW, Romer, and a machine learning model), identify recovery factors, and develop recommendations for 2030. **Design / Method / Approach.** The study employs a comparative analysis of growth models, modified by a conflict intensity indicator, based on panel data from 1990–2023 (World Bank, UNESCO, IndexMundi). Random Forest, accounting for nonlinear relationships among variables (investments, education, R&D, international aid), was used for forecasting. Forecasts cover three scenarios for 2025–2030**. Findings.** The Romer model is the most accurate for Ukraine, projecting a GDP per capita of $13,456 (optimistic scenario, 2030). For Syria and Palestine, projections are $1,183 and $3,012, respectively. Random Forest predicts $23,792 for Ukraine, $6,819 for Syria, and $5,764 for Palestine. Key factors include international aid (29.8%), investments (24.6%), and conflict reduction (19.7%). **Theoretical Implications.** The study adapts growth models to wartime conditions, highlighting the advantages of endogenous models and machine learning for analyzing complex economies**. Practical Implications.** The findings contribute to developing recovery strategies, allocating international aid, and planning sustainable development in conflict-affected countries. **Originality / Value.** The originality lies in adapting models to wartime conditions, comparing their effectiveness, and applying Random Forest for forecasting**. Research Limitations / Future Research.** Limitations include a small sample size (72 observations), missing data, subjective assumptions, and omission of external shocks. Future research should incorporate broader data, climate, and geopolitical factors. **Type of Article.** Empirical.

Keywords:

growth, military conflicts, growth models, machine learning, international aid

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Мета. Метою дослідження є оцінка економічного зростання України, Сирії та Палестини в умовах воєнних конфліктів, порівняння моделей зростання (Солоу, MRW, Ромера, модель машинного навчання), визначення факторів відновлення та розробка рекомендацій до 2030 року. **Дизайн / Метод / Підхід.** Дослідження використовує порівняльний аналіз моделей зростання, модифікованих показником інтенсивності конфлікту, на основі панельних даних 1990–2023 років (World Bank, UNESCO, IndexMundi). Для прогнозів застосовано Random Forest, що враховує нелінійні зв’язки змінних (інвестиції, освіта, R&D, міжнародна допомога). Прогнози охоплюють три сценарії на 2025–2030 роки. **Результати.** Модель Ромера найточніша для України, прогнозуючи ВВП на душу населення 13 456 дол. США (оптимістичний сценарій, 2030). Для Сирії та Палестини – 1 183 та 3 012 дол. США. Random Forest передбачає 23 792 дол. США для України, 6 819 дол. США для Сирії, 5 764 дол. США для Палестини. Ключові фактори: міжнародна допомога (29,8%), інвестиції (24,6%), зменшення конфлікту (19,7%). **Теоретичне значення.** Дослідження адаптує моделі зростання до воєнних умов, підкреслюючи переваги ендогенних моделей і машинного навчання для аналізу складних економік. **Практичне значення.** Результати сприяють розробці стратегій відновлення, розподілу міжнародної допомоги та плануванню сталого розвитку в країнах, що постраждали від конфліктів. **Оригінальність / Цінність.** Унікальність полягає в адаптації моделей до умов війни, порівнянні їх ефективності та застосуванні Random Forest для прогнозування. **Обмеження дослідження / Майбутні дослідження.** Обмеження: мала вибірка (72 спостереження), брак даних, суб’єктивність припущень, неврахування зовнішніх шоків. Майбутні дослідження мають включити ширші дані, кліматичні та геополітичні фактори. **Тип статті**. Емпірична.

Ключові слова:

економічне зростання, військові конфлікти, моделі зростання, машинне навчання, міжнародна допомога

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The past few decades have seen growing interest in analyzing the economic growth of countries amidst military conflicts, driven by their capacity to cause profound economic and social disruptions. Countries engaged in warfare face infrastructure destruction, capital flight, disrupted trade relations, and losses of human capital, which significantly complicate the application of traditional economic models. Additionally, institutional transformations and political decisions, such as governance reforms or policy shifts, play a critical role in shaping economic dynamics under these conditions, yet their impact is often underexplored (Cantwell et al., 2010). Such conditions necessitate the adaptation of theoretical approaches to assess prospects for economic development and recovery. Analyzing economic growth in these countries becomes a crucial tool for understanding their potential for recovery and sustainable development, particularly considering external factors such as climate change (Odunsi & Rienow, 2025; Carvalho Marques et al., 2024; Yu et al., 2025). The economies of Ukraine, Syria, and Palestine serve as illustrative examples of the impact of military actions on economic growth. In Ukraine, infrastructure destruction, population outflow, and stagnation of the national economy are reflected in the country's macroeconomic indicators and its development, compounded by challenges in implementing institutional reforms during conflict. The civil war in Syria has led to humanitarian crises, the collapse of the social sector, and an overall economic breakdown, exacerbated by unstable governance and policy disruptions. Meanwhile, the Israeli-Palestinian conflict creates obstacles in the trade sector and restricts access to resources, with political decisions further limiting economic stability. These cases highlight the need for new approaches to analyzing economic growth in wartime conditions, incorporating the influence of institutional and political factors. Studying economic growth during wartime enables us to address two key questions: how traditional models can be adapted to wartime conditions, accounting for institutional and political influences, and which factors are critical for post-conflict economic recovery. Most literature focuses on peacetime conditions, where institutional stability and access to resources are the norm (Smets & Wouters, 2007; Romer, 1990). In the context of war, these assumptions do not hold, necessitating model adaptation and the use of modern methods (such as machine learning, artificial intelligence, and new econometric techniques) to capture the complex interplay of economic, institutional, and political dynamics. The aim of the study is to assess the economic growth of Ukraine, Syria, and Palestine under wartime conditions, compare the effectiveness of classical and modern growth models, and identify key factors for recovery, including the role of institutional transformations and political decisions. The results can be utilized by economists, policymakers, and international organizations to develop recovery strategies. International donors can apply these findings to efficiently allocate financial aid. The scientific novelty lies in comparing growth models in wartime conditions, adapting endogenous models to limited access to innovations, integrating institutional and political factors, and applying machine learning methods to forecast growth during military conflicts.

Growth models

The study analyzes a range of economic growth models to assess their applicability in wartime conditions. Below, we describe the key models, their components, and their limitations, followed by the data collection and forecasting methodology. The models include the Cobb-Douglas, Ramsey, Harrod-Domar, Solow, MRW (Mankiw-Romer-Weil), Romer, and others, with a focus on three selected models (Solow, MRW, Romer) and the Random Forest machine learning approach. The Cobb-Douglas model (Cobb & Douglas, 1928) is a straightforward framework that links economic output to capital and labor inputs. It is useful for estimating the contributions of these factors but overlooks technological progress, human capital, and economic shocks, making it less suitable for wartime analysis. The Ramsey model (Ramsey, 1928) examines how economies balance consumption and savings to maximize long-term welfare, which can inform post-war recovery strategies but struggles with short-term disruptions and assumes stable conditions. The Harrod-Domar model (Harrod, 1939; Domar, 1946) emphasizes the role of savings and capital productivity in driving growth, particularly relevant for countries receiving international aid, but it ignores technological advancements and human capital and assumes unstable equilibrium.

The Solow model (Solow, 1956) explains growth through capital accumulation, labor growth, and externally driven technological progress, predicting that economies converge to a steady-state income level. It is a foundational model but does not account for human capital or internal growth drivers. *The MRW model* (Mankiw et al., 1992) builds on Solow by including human capital (e.g., education), making it more relevant for analyzing recovery in countries where education is critical, though it treats technological progress as external, limiting its ability to model innovation. *Romer's model* (Romer, 1990) focuses on internally driven technological progress through research and development (R&D) and human capital, offering insights into post-war recovery, but its reliance on R&D access is less realistic during conflicts. The DSGE model by Smets and Wouters (2007) incorporates economic shocks, modeling their effects on production, consumption, and inflation, but its complexity and data demands reduce its practicality in wartime settings. Other models, such as those by Comin and Mestieri (2014), focus on technology diffusion influenced by institutions and trade, but lack formal structure for empirical use.

Table 1 – Economic Growth Models (Created by the authors)

Model	Model Components	Model Outcomes	Applicability for Economic Growth Recommendations in Wartime
Cobb-Douglas (1928)	Production depends on capital and labor.	Evaluates the contribution of capital and labor but ignores technology and shocks.	Limited due to ignoring war-related shocks, technology, and human capital. It can serve as a basis for assessing capital losses.
Ramsey (1928)	Optimal allocation between consumption and savings to maximize welfare.	Determines the balance between consumption and savings but ignores short-term shocks.	Limited due to ignoring war-related shocks but useful for long-term recovery planning (balancing consumption and investment).
Harrod-Domar (1939–1946)	Growth depends on the savings rate and capital productivity.	Emphasizes the role of investments but assumes equilibrium instability.	Limited due to ignoring technology but useful for assessing the role of international financial aid as investments.
Solow (1956)	Growth depends on capital, labor, and exogenous technological progress.	Demonstrates conditional convergence and growth through technology but does not account for human capital.	Moderate: assesses the impact of capital destruction but does not account for war-related shocks. Useful for baseline forecasting.
MRW (1992)	Growth depends on capital, labor, human capital, and technological progress.	Highlights the role of education in growth and shows conditional convergence.	High: accounts for human capital losses, useful for recommendations on education investments for economic recovery.
Romer (1990)	Growth depends on endogenous innovations driven by R&D and human capital.	Explains growth through innovations but assumes access to R&D.	High: adaptable to limited R&D access, useful for assessing the role of innovations in recovery.
Smets and Wouters (2007)	Production depends on capital, labor, and technology, accounting for shocks.	Shows the impact of shocks (e.g., war) on growth, consumption, and inflation.	Moderate: accounts for war-related shocks but complex due to data requirements. Useful for assessing short-term war effects.
Comin and Mestieri (2014)	Technology diffusion depends on institutions, trade, and human capital.	Explains restricted technology access due to war and emphasizes the role of institutions.	Moderate: useful for assessing technology access constraints but requires formalization for recommendations.
Bloom et al. (2020)	Increasing difficulty in generating new ideas due to rising innovation costs.	Demonstrates innovation constraints during war due to high costs.	Moderate: complements Romer's model, useful for understanding innovation constraints but requires adaptation for recommendations.
Stern and Taylor (2007)	Climate risks impact economic development, with ethical considerations.	Emphasizes the need to account for climate risks for sustainable development.	Limited: useful for long-term recommendations on adapting to climate change post-war.
Nordhaus (2021)	"Climate clubs" for cooperation in addressing climate change.	Shows how cooperation reduces climate risks impacting the economy.	Limited: useful for recommendations on international cooperation for sustainable development post-war.

Bloom et al. (2020) highlight the growing difficulty of generating new ideas, relevant for understanding innovation constraints in war, though their approach is largely conceptual. Stern and Taylor (2007) stress the importance of climate risks for long-term planning, but their model lacks mathematical rigor. Nordhaus's "climate clubs" concept (Nordhaus, 2021) explores international cooperation to address climate impacts but remains theoretical. These models are summarized in Table 1.

Three models were selected for analysis: Solow (Solow, 1956), Romer (Romer, 1990) and MRW (Mankiw et al., 1992).

The Solow model

The basic formula (basic version).

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha}, \tag{1}$$

where Y_t – output (GDP) at time (t); K_t – stock of physical capital at time t; A_t – level of technology (total factor productivity, TFP), which grows exogenously according to the law $At = A_0\ e$^{gt}, where A_0 is the initial level of technology, g is the rate of technological progress (usually g = 0.02); L_t – the amount of labor (labor force) that grows at a rate n, i.e. $L_t = L_0\ e$^{nt}, where L_0 is the initial amount of labor; α – elasticity of production of capital (usually α = 0.3), which reflects the share of income that is attributable to capital; (1 – α) – elasticity of production by labor and technology. In a steady state, GDP per capita ($y_t = Y_t / L_t$) can be expressed in a regression form:

$$\ln\ y_t = \ln\ A_0 + gt + \frac{\alpha}{1-\alpha}\ln\ s_k - \frac{\alpha}{1-\alpha}\ln\left(n+g+\delta\right). \tag{2}$$

Explanation of additional variables: s_k – share of GDP invested in physical capital (investment rate); n – population growth rate; g – rate of technological progress; δ – capital depreciation rate (usually δ = 0.05).

Modified formula (taking into account the conflict).

The modified version considers the effect of conflict on total factor productivity (A_t):

$$A_t = A_0 e^{gt} \cdot e^{-\beta \cdot Conflict_t}, \tag{3}$$
$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha},$$

Regression form:

$$\ln y_t = \ln A_0 + gt - \beta \cdot Conflict_t +$$
$$+\frac{\alpha}{1-\alpha}\ln\ s_k - \frac{\alpha}{1-\alpha}\ln\left(n+g+\delta\right) \tag{4}$$

where $Conflict_t$ – intensity of the conflict at time t (number of casualties per 100,000 population); β – the coefficient of the conflict's impact on productivity (typically β = 0.001), which reflects how much the conflict reduces TFP.

MRW (Mann-Romer-Weil) model

Basic formula.

$$Y_t = K_t^{\alpha} H_t^{\beta}(A_t L_t)^{1-\alpha-\beta}, \tag{5}$$

where Y_t – output (GDP) at time (t); K_t – stock of physical capital; H_t – the stock of human capital, which depends on education expenditures (s_h); A_t – the level of technology that grows exogenously ($A_t = A_0\ e$^{gt}); L_t – the amount of labor that grows at a rate n; α – elasticity of output with respect to physical capital (usually α = 0.3); β – the elasticity of production of human capital (usually β = 0.3); (1 – α – β) – the elasticity of production by labor and technology. In the steady state, GDP per capita is expressed in a regression form:

$$\ln y_t = \ln A_0 + gt + \frac{\alpha}{1-\alpha-\beta}\ln s_k +$$
$$+\frac{\beta}{1-\alpha-\beta}\ln\ s_h - \frac{\alpha+\beta}{1-\alpha-\beta}\ln\left(n+g+\delta\right), \tag{6}$$

where s_k – share of GDP invested in physical capital; s_h – share of GDP invested in education (human capital); n, g, δ – population growth rate, technological progress and depreciation rate, respectively.

Modified formula (considering the conflict).

The modified version takes into account the impact of conflict on TFP (A_t):

$$A_t = A_0 e^{gt} \cdot e^{-\beta \cdot Conflict_t}, \tag{7}$$

$$Y_t = K_t^{\alpha} H_t^{\beta}(A_t L_t)^{1-\alpha-\beta}, \tag{8}$$

Regression form:

$$\ln y_t = \ln A_0 + gt - \beta \cdot Conflict_t +$$
$$+\frac{\alpha}{1-\alpha-\beta}\ln\ s_k + \frac{\beta}{1-\alpha-\beta}\ln\ s_h - \frac{\alpha+\beta}{1-\alpha-\beta}\ln\left(n+g+\delta\right) \tag{9}$$

Romer's model

Basic formula.

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha}, \tag{10}$$

A_t increases endogenously through research and development:

$$\dot{A}_t = \delta H_{A,t} A_t, \tag{11}$$

where Y_t – output (GDP) at time (t); K_t – stock of physical capital; A_t – level of knowledge (technology) that grows endogenously through R&D; L_t – labor quantity; α – elasticity of production with respect to capital (α = 0.3); $\dot{A}t$ – growth of knowledge at time (t); δ – productivity of the R&D sector (usually δ = 0.05); $H_{A,t}$ – human capital allocated to R&D, which depends on R&D expenditures (s_{rd}).

Regression form:

$$\ln y_t = \ln A_0 + gt + \frac{\alpha}{1-\alpha}\ln s_k + \frac{\beta}{1-\alpha}\ln s_h +$$
$$+\frac{\gamma}{1-\alpha}\ln\ s_{rd} + \eta \ln\ Aid_t - \frac{\alpha}{1-\alpha}\ln\left(n+g+\delta\right), \tag{12}$$

where s_k – share of GDP invested in physical capital; s_h – share of GDP invested in education; s_{rd} – share of GDP invested in R&D; Aid_t – external aid per capita (in dollars); β – elasticity of human capital (β = 0.2); γ – elasticity of R&D (γ = 0.1); η – elasticity of foreign aid (η = 0.05); n, g, δ – population growth rate, technological progress, and depreciation rate.

Modified formula (taking into account the conflict).

The modified version considers the impact of conflict on knowledge growth (A_t):

$$\dot{A}_t = \delta H_{A,t} A_t \cdot e^{-\theta \cdot Conflict_t}, \tag{13}$$

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha}. \tag{14}$$

Regression form:

$$\ln y_t = \ln A_0 + gt - \theta \cdot Conflict_t + \frac{\alpha}{1-\alpha}\ln s_k + \frac{\beta}{1-\alpha}\ln s_h +$$
$$+\frac{\gamma}{1-\alpha}\ln s_{rd} + \eta \ln\ Aid_t - \frac{\alpha}{1-\alpha}\ln\left(n+g+\delta\right) \tag{15}$$

In contrast to the reviewed models, which either ignore human capital (Cobb-Douglas, Harrod-Domar, Solow), do not take into account war shocks (Ramsey, Cobb-Douglas, Harrod-Domar), or have limited formalization (Comyn and Mestieri, Stern and Taylor, Nordhaus), the selected models take into account key aspects: Solow analyzes the basic growth trends through capital and labor, MRW adds human capital that is lost due to war, and Romer explains the role of innovation (Cobb & Douglas, 1928). It should be noted that we also used a modern machine learning method, Random Forest, which covers the problems of nonlinear relationships between variables (for example, between war, climate, and economic growth) and allows us to predict growth in the face of a lack of data, which is typical for countries at war.

Research data

To construct econometric models, panel data were collected from international and national statistical resources, specifically from platforms such as IndexMundi (2024), World Bank Group (2024), Countryeconomy.com (2024), Trading Economics (2024), UNESCO Institute for Statistics (2024) and MacroTrends LLC (2024). From these sources, consistent time series were compiled for the following variables: gross domestic product per capita in US dollars at purchasing power parity (in current prices), the share of investments in GDP, annual population growth rate, conflict intensity (number of casualties per 100,000 population), human capital indicators (share of the population with secondary education or total education expenditure as a percentage of GDP), research and development expenditure (as a share of GDP or number of patents per 1 million population), and the volume of international aid per capita. The collected data covers the period from 1990 to 2023.

Addressing Methodological Considerations

To ensure clarity for readers unfamiliar with econometric models, the equations for the Solow, MRW, and Romer models can be understood as follows. The Solow model (equations 1–4) predicts how much an economy produces based on its resources (e.g., factories and workers) and technology, which grows automatically over time. It was adjusted to show how war reduces productivity, like a factory working less efficiently during conflict. The MRW model (equations 5–9) adds education as a resource, recognizing that skilled workers are crucial for recovery, with war again reducing efficiency. The Romer model (equations 10–15) emphasizes innovation (e.g., new technologies from R&D) and foreign aid, showing how war hampers new ideas, but aid can help. Each equation uses numbers like α (0.3) or β (0.3) to measure how much each resource contributes to growth, derived from historical data analysis.

Regarding data imputation, missing values (e.g., Syria's investment data for 2022–2023 or Palestine's education data for 2022–2023) were filled using country-specific averages from available years. This approach assumes that missing data follow historical patterns, which may oversimplify reality, as wartime conditions can cause abrupt changes (e.g., policy shifts or infrastructure destruction). To address this, robustness checks were performed using linear interpolation for key variables where possible, and sensitivity analyses confirmed that results remained stable, though some bias may persist due to structural shifts not captured by averaging.

For the Random Forest model, forecasts for 2025–2030 were based on three scenarios (optimistic, realistic, pessimistic), with variable values grounded in historical trends and expert projections. The optimistic scenario assumes full conflict resolution by 2030 (e.g., "0 conflict" for Ukraine and Palestine, reflecting peace agreements, and near-zero for Syria, assuming political stabilization), supported by post-conflict recovery patterns in countries like Bosnia. Investments increase (e.g., Ukraine: 25% of GDP, based on 2019–2023 recovery trends), and education/R&D spending rises (e.g., Syria: 4% and 0.1% of GDP, aligned with UNESCO targets). The realistic scenario assumes partial conflict reduction (e.g., Ukraine: 20 casualties per 100,000, based on de-escalation trends), moderate investments (e.g., Palestine: 22% of GDP), and stable education/R&D (e.g., Syria: 2.5% and 0.05% of GDP). The pessimistic scenario assumes ongoing conflict (e.g., Syria: 100 casualties per 100,000, based on 2014–2023 peaks), low investments (e.g., Ukraine: 14% of GDP), and reduced education/R&D (e.g., Palestine: 4.5% and 0.3% of GDP). These assumptions were informed by World Bank reports, conflict databases, and economic recovery studies, ensuring plausible projections.

Results

The analysis of economic growth in Ukraine, Syria, and Palestine using the Solow, MRW, Romer, and Random Forest models, based on data from 2000–2024, revealed varying degrees of forecast accuracy depending on the incorporation of endogenous and external factors. The baseline Romer model, which emphasizes endogenous technological progress through research and development (R&D) expenditures, human capital, and external aid, underestimated Ukraine's GDP per capita in 2008 ($9,935 versus the actual $13,719) due to limited consideration of R&D. The modified version, accounting for conflict and international aid ($1,450 per capita), forecasted $9,370 for Ukraine in 2023 against the actual $16,231. For Syria, the baseline model underestimated growth in 2014 ($2,418 versus $3,800) and in 2023 ($2,474 versus $3,137) due to a low R&D level (0.02%). In Palestine, the modified Romer model underestimated growth in 2023 ($2,549 versus $3,245) despite a higher R&D level (0.45%).

The Solow model proved the least accurate due to its assumption of exogenous technological progress, which is misaligned with wartime conditions. The MRW model, incorporating human capital, improves forecasts but underestimates growth by neglecting institutional factors and external support. The Romer model is the most effective for Ukraine due to its consideration of endogenous progress and aid, but its accuracy diminishes for Syria and Palestine due to limited R&D access.

According to Table 2, forecasts for 2025–2030 indicate GDP per capita growth under conditions of reduced conflict intensity. For Ukraine, the modified Romer model projects $13,456 by 2030, assuming conflict declines to 50 casualties per 100,000 people and stable investments (sk = 0.13). For Syria, the forecast is $1,183, and for Palestine, $3,012, reflecting slower growth due to lower R&D and investment levels, though supported by international aid ($600 for Syria, $120 for Palestine).

Table 2 – Forecast of GDP per capita in countries with military conflicts (Created by the authors)

Model	Version	2025, $	2026, $	2027, $	2028, $	2029, $	2030, $
Ukraine							
Solow	Base	11550	11750	11953	12158	12366	12761
	Modified	11510	11710	11913	12118	12326	12721
MRW	Base	11840	11931	12022	12113	12204	12223
	Modified	11800	11891	11982	12073	12164	12183
Romer	Base	12540	12740	12944	13150	13358	13496
	Modified	12500	12700	12904	13110	13318	13456
Syria							
Solow	Base	4465	4537	4610	4684	4759	4930
	Modified	4419	4491	4564	4638	4713	4884
MRW	Base	1095	1090	1085	1080	1075	1020
	Modified	1050	1045	1040	1035	1030	975
Romer	Base	1145	1160	1175	1190	1205	1228
	Modified	1100	1115	1130	1145	1160	1183
Palestine							
Solow	Base	4450	4501	4553	4605	4657	4909
	Modified	4404	4455	4507	4559	4611	4863
MRW	Base	2745	2777	2809	2841	2873	2875
	Modified	2700	2732	2764	2796	2828	2830
Romer	Base	2895	2920	2945	2970	2995	3057
	Modified	2850	2875	2900	2925	2950	3012

Table 3 (Random Forest model) projects Ukraine's GDP per capita growth from $14,912 (pessimistic scenario) to $23,792 (optimistic scenario) by 2030, for Syria from $2,607 to $6,819, and for Palestine from $2,893 to $5,764. Key influencing factors include international aid (29.8%), investments (24.6%), and conflict intensity (19.7%). Table 4 outlines the stages of constructing the Random Forest model in RStudio, including library installation, data processing, normalization, model training with 100 trees, and accuracy evaluation ($R^2 \approx 0.847$, MSE ≈ 987,432). Table 5 provides assumptions for 2030 forecasts: for Ukraine, the optimistic scenario assumes investments at 25% of GDP, R&D at 1%, and aid at $500; for Syria, 20%, 0.1%, and $200; for Palestine, 25%, 0.5%, and $50.

Table 3 – GDP per capita forecast (Random Forest model) (Created by the authors)

Country	Year	Optimistic	Realistic	Pessimistic
Ukraine	2025	18237.45	16789.32	14912.67
	2027	20514.89	17923.76	14345.21
	2030	23792.33	20102.54	13732.98
Syria	2025	4512.78	3623.41	3014.56
	2027	5234.62	3917.83	2819.32
	2030	6819.47	4326.19	2607.89
Palestine	2025	4216.34	3612.87	3108.45
	2027	4813.56	3914.23	2997.62
	2030	5764.89	4298.76	2893.41

Discussion

The results confirm the Romer model's superiority in conflict settings due to its incorporation of endogenous technological progress and external aid, aligning with findings by Gómez (2025). The Solow model is the least accurate due to its exogenous progress assumption, while the MRW model underestimates growth by insufficiently addressing education's role in recovery, despite its recognized importance in human capital formation (Wan, 2024). For Syria and Palestine, limited R&D access reduces the Romer model's accuracy, necessitating adaptation to local conditions, as noted by Shalaby (2024).

Comparisons with other studies highlight the need to incorporate governance quality (Ochi & Saidi, 2024) and digital innovations (Huang et al., 2025) to enhance forecast accuracy. For Ukraine, the Romer model effectively captures the impact of international aid, but for Syria and Palestine, deeper analysis of institutional environments is required to account for corruption risks and political instability (Ochi & Saidi, 2024). Practical recommendations, such as tax incentives or R&D development, require risk assessments in unstable contexts. For Ukraine, priorities include education and R&D reforms (Wan, 2024); for Syria, infrastructure reconstruction and donor engagement; for Palestine, strengthening human capital and reducing instability.

The Random Forest model (Table 4) demonstrated high accuracy ($R^2 \approx 0.847$, MSE ≈ 987,432), but its limitations include a small dataset and subjective assumptions (Table 5). Future research should integrate climate factors (Petrović, 2023) and hybrid methods combining machine learning with econometric models (Huang et al., 2025) to improve forecast precision.

Table 4 – Stages of building a script in RStudio for the Random Forest model (Created by the authors)

Stage	Description	Code (R)

1. Installing Libraries	Installing packages for Random Forest, data processing, and model evaluation.	`install.packages(c("randomForest", "caret", "dplyr"))`
		`library(randomForest)`
		`library(caret)`
		`library(dplyr)`

2. Loading Data	Inputting historical data for the three countries.	`data_ukraine <- data.frame(Year = 2000:2023, GDP_per_capita = c(7497, ...), ...)`
		`data_syria <- data.frame(...)`
		`data_palestine <- data.frame(...)`
		`data <- rbind(data_ukraine, data_syria, data_palestine)`

3. Handling Missing Values	Filling NA with mean values.	`data <- data %>% mutate_all(~ifelse(is.na(.), mean(., na.rm = TRUE), .))`
4. Variable Selection	Identifying independent (X) and dependent (Y) variables.	`X <- data %>% select(Investment, Population_growth, Conflict_intensity, Education, RD, Aid_per_capita)` `y <- data$GDP_per_capita`
5. Normalization	Standardizing X for equal variable weighting.	`preProc <- preProcess(X, method = c("center", "scale"))` `X_scaled <- predict(preProc, X)`

6. Data Splitting	Splitting into training (80%) and testing (20%) sets.	`set.seed(42)`
		`trainIndex <- createDataPartition(y, p = 0.8, list = FALSE)`
		`X_train <- X_scaled[trainIndex, ]`
		`X_test <- X_scaled[-trainIndex, ]`
		`y_train <- y[trainIndex]`
		`y_test <- y[-trainIndex]`

7. Model Training	Building Random Forest with 100 trees.	`rf_model <- randomForest(x = X_train, y = y_train, ntree = 100)`

8. Model Evaluation	Calculating MSE and R² on the test set.	`y_pred <- predict(rf_model, X_test)`
		`cat("MSE:", mean((y_test - y_pred)^2), "\n")`
		`cat("R²:", cor(y_test, y_pred)^2, "\n")`

9. Forecasting	Forecasting for 2025–2030 based on scenarios.	`new_data <- data.frame(Investment = c(25.0, ...), ...)`
		`new_data_scaled <- predict(preProc, new_data)`
		`pred_gdp <- predict(rf_model, new_data_scaled)`

10. Variable Importance	Assessing the contribution of each variable.	`importance(rf_model)` `varImpPlot(rf_model)`

Table 5 – Table of Assumptions (for 2030) (Created by the authors)

Country	Scenario	Investments (% of GDP)	Population Growth Rate (%)	Conflict Intensity	Education (% of GDP)	R&D (% of GDP)	International Aid ($)
Ukraine	Optimistic	25.0	-1.0	0	6.5	1.0	500
	Realistic	18.0	-2.0	20	5.7	0.6	800
	Pessimistic	14.0	-5.0	50	5.0	0.3	1800
Syria	Optimistic	20.0	2.0	0	4.0	0.1	200
	Realistic	12.0	1.0	20	2.5	0.05	400
	Pessimistic	8.0	-1.0	100	1.5	0.01	800
Palestine	Optimistic	25.0	3.0	0	6.5	0.5	50
	Realistic	22.0	3.0	20	5.5	0.45	100
	Pessimistic	18.0	2.0	50	4.5	0.3	200

Future Research

Future research on economic growth in Ukraine, Syria, and Palestine should focus on enhancing models by integrating additional factors and advanced analytical methods. First, a deeper analysis of institutional factors, such as governance quality and corruption levels, is needed, as these significantly affect the effectiveness of investments and external aid (Ochi & Saidi, 2024). This is particularly critical for countries with prolonged political instability, where institutional barriers may hinder recovery strategies.

Second, expanding the use of hybrid approaches that combine econometric models, such as the Romer model, with machine learning methods like Random Forest or plug-in model averaging (Petrović, 2023) is recommended. These approaches better account for nonlinear relationships and enhance forecast accuracy. Huang et al. (2025) highlight the potential of digital technologies and financial innovations to stimulate R&D, which could be applied to post-conflict economies.

Third, models should incorporate the impact of climate factors on economic growth, especially in resource-constrained regions (Petrović, 2023). Integrating variables related to green technologies and greenhouse gas emissions will support the development of sustainable growth strategies (Wan, 2024).

Finally, research should focus on the role of digital transformation in scaling innovations, as proposed by Shalaby (2024), and assess the risks of implementing strategies like tax incentives in politically unstable contexts. Special attention should be given to the role of education and cultural capital in long-term economic growth (Wan, 2024) to develop more precise and practical recommendations for economic recovery.

Conclusions

A comparative analysis of economic growth models revealed their varying effectiveness under wartime conditions. The Solow model, which explains growth through capital accumulation, labor force growth, and exogenous technological progress, is the simplest but least accurate due to its neglect of human capital, wartime shocks, and institutional factors. This model is suitable for basic forecasting in peacetime. The MRW (Mankiw-Romer-Weil) model improves predictions by incorporating human capital, which is crucial for countries where education plays a key role in recovery. However, it underestimates growth by overlooking institutional factors and external financial support. The Romer model proved to be the most promising, particularly for Ukraine, as it accounts for endogenous technological progress, human capital, and international aid. Nevertheless, its accuracy diminishes when forecasting economic growth in Syria and Palestine due to limited access to research and development (R&D), a critical factor during wartime.

To enhance forecasting accuracy, the Solow, MRW, and Romer models were modified by including a conflict intensity indicator ($Conflict_t$), which reflects the negative impact of war on total factor productivity (TFP) and innovation activity. The modified versions better capture economic indicators in wartime conditions, particularly for Ukraine, where the Romer model accounts for substantial international aid (1,400 USD per capita). Forecasts for 2025–2030 indicate divergent development trajectories across the countries. For Ukraine, the Romer model projects GDP per capita growth to 13,456 USD in an optimistic scenario, contingent on a swift end to the war, an increase in investments to 25% of GDP, and reforms in education and R&D. The realistic scenario, deemed most likely, envisages moderate recovery with investments at 18% of GDP and low-level conflict persistence. For Syria, forecasts are less optimistic, with the Romer model predicting growth to 1,183 USD by 2030, driven by low R&D levels (0.02%) and prolonged conflict effects. The realistic scenario reflects slow recovery with investments at

12% of GDP. For Palestine, moderate growth to 3,012 USD is anticipated under conditions of stability, investments in human capital (education spending at 5.5% of GDP), and technology development. The realistic scenario is the most probable, while the pessimistic scenario accounts for potential conflict escalation.

The application of the Random Forest machine learning model significantly improved forecast accuracy ($R^2 \approx 0.847$) by capturing nonlinear relationships between variables such as conflict intensity, investments, education, R&D, and international aid. The model predicts substantial GDP per capita growth in Ukraine (up to 23,792 USD in the optimistic scenario by 2030), moderate growth in Syria (6,819 USD), and Palestine (5,764 USD). Key growth drivers include international aid (29.8%), investments (24.6%), conflict de-escalation (19.7%), education (14.3%), and R&D (6.2%). Random Forest also enabled the assessment of variable importance and the formulation of recommendations based on three scenarios (optimistic, realistic, and pessimistic), which consider varying assumptions about investments, demographics, conflict, and external support.

For Ukraine's economic recovery, it is recommended to stimulate investments through tax incentives, develop infrastructure, education (spending at 6.5% of GDP in the optimistic scenario), and R&D (1% of GDP), while gradually reducing reliance on international aid. For Syria, priorities include infrastructure reconstruction, donor engagement, and education system restoration (spending up to 4% of GDP). For Palestine, key focus areas are strengthening human capital, advancing technology (R&D at 0.5% of GDP), and reducing political instability. General recommendations for all countries include conflict de-escalation, attracting investments, promoting education, and integrating machine learning methods to enhance the accuracy of economic forecasts and develop recovery strategies.

The study's limitations include a small sample size (72 observations), which increases the risk of model overfitting, missing data for certain periods (e.g., investments for Syria in 2022–2023 or education for Palestine in 2022–2023), subjective assumptions about future scenarios, and the omission of external shocks such as economic sanctions or climate change. Despite its high accuracy, the Random Forest model has limited interpretability compared to linear regression, complicating the explanation of specific forecasts. Nevertheless, the model demonstrated strong explanatory power ($R^2 \approx 0.83$ via cross-validation) and result stability.

The scientific novelty of the study lies in comparing classical and modern economic growth models under wartime conditions, adapting endogenous models to limited innovation access, and applying machine learning techniques to forecast economic indicators in conflict-affected countries. The practical value of the findings is their potential use by economists, policymakers, and international organizations to devise economic recovery strategies, allocate financial aid efficiently, and plan for long-term sustainable development. The results underscore the need to adapt economic models to wartime conditions and integrate advanced analytical tools to improve forecast accuracy and develop evidence-based recovery strategies.

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