Estimation of Ukrainian Refugees Impact on COVID-19 Dynamics in Czech Republic using Prophet Model

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Abstract

This study aims to examine the impact of the Russian invasion of Ukraine on the epidemiological trajectory of COVID-19, demonstrating the interplay between geopolitical instability and infectious disease dynamics. We developed a machine learning model adapted to incorporate the onset of military conflict into its predictive framework. The model's performance was evaluated against actual COVID-19 morbidity and mortality data before and after the invasion, considering a set of identified epidemiological and conflict-related variables. The predictive accuracy of COVID-19 cases showed a marked decline post-invasion, highlighting the perturbing effect of the conflict on disease spread dynamics. Conversely, the mortality predictions exhibited increased accuracy, suggesting a differential impact of the conflict on various aspects of the epidemic process. The study's findings underscore the necessity of revising epidemiological models in conflict scenarios. It illustrates that incorporating geopolitical events can significantly alter predictive outcomes and, therefore, should be considered in public health planning and response strategies. The research calls for expanded models that can dynamically integrate various global sociopolitical disturbances and for interdisciplinary efforts to create robust forecasting tools capable of adapting to rapidly changing conditions.

Keywords

COVID-19, Prophet, machine learning, deep learning, war, epidemic model

1. Introduction

The COVID-19 pandemic has been a significant event worldwide, leading to widespread challenges and major changes in how we handle public health, the economy, and social interactions [1]. It has forced us to look closely at our healthcare systems and has pushed quick advancements in technology and science. The pandemic has affected everyday life, international travel, and the movement of goods worldwide, showing how closely connected we all are [2]. It has also highlighted the need for countries to work together to handle such global crises. The importance of the COVID-19 pandemic extends beyond its immediate impact; it has important lessons for how we make policies, prepare for emergencies, and view health as an essential part of our overall safety and well-being [3].

The COVID-19 pandemic's trajectory within the Czech Republic has been characterized by several distinctive phases, mirroring global trends while exhibiting unique national peculiarities [4]. Initially, the country was lauded for its prompt response to the initial outbreak, employing stringent measures such as border closures, mandatory mask usage, and early lockdowns, which effectively curtailed the spread of the virus [5]. However, the subsequent waves of infection

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witnessed a reversal of fortune as the nation grappled with rising cases, highlighting the strains on its healthcare system [6]. The public health strategy oscillated between various levels of restrictions, reflecting a balance between epidemiological caution and socio-economic pressures. The pandemic further acted as a catalyst for the Czech Republic to enhance its healthcare infrastructure, accelerate digital transformation in the provision of health services, and refocus on the importance of epidemiological forecasting and preventive measures [7]. The national response evolved, incorporating lessons from earlier phases to inform policy adaptations and health directives aimed at mitigating the pandemic's impact and facilitating a recovery path focused on resilience and health security [8].

The Russian invasion of Ukraine has severely exacerbated the COVID-19 crisis during a critical phase of the Omicron variant's spread [9]. Predicted to face thousands of new cases daily, Ukraine's healthcare system has been overwhelmed by the dual challenges of war and the pandemic [10]. Medical facilities in conflict zones have been destroyed or rendered inoperative, hindering the identification and diagnosis of COVID-19 cases, which has led to a substantial underreporting of the actual infection rates [11]. Hospital capacities have been strained as beds and resources allocated for COVID-19 patients are now redirected to treat those wounded in the conflict, curtailing the treatment options for the virus and limiting access to essential medicines and oxygen [12].

Moreover, standard public health measures such as social distancing and mask-wearing have become nearly impossible to enforce, especially for individuals in bomb shelters or during evacuations, which has likely intensified the virus's spread [13]. The invasion has also brought Ukraine's vaccination campaign to a standstill, particularly in areas of active conflict, causing a further decline in preventative measures against COVID-19.

The convergence of the war and the pandemic has shifted the focus of Ukraine's healthcare system away from the virus, prioritizing immediate survival and care for injuries over pandemic control [14]. This has inadvertently led to an increase in the virus's transmission, compounding the country's humanitarian crisis.

Integrating information technologies and simulation models has been instrumental in combating the pandemic, providing vital tools for forecasting, decision-making, and managing healthcare resources [15]. Simulation models, leveraging vast datasets, have been pivotal in predicting the spread of the virus, enabling governments and healthcare organizations to enact preemptive measures and optimize response strategies [16]. Information technologies, such as AI and machine learning, have facilitated the real-time analysis of infection rates, hospitalization, and resource utilization, enhancing the ability to anticipate and respond to emerging hotspots [17]. Furthermore, digital contact tracing apps have aided in mitigating transmission by identifying and alerting individuals who may have been exposed to the virus [18]. These technological approaches, when combined with robust data analytics, have not only contributed to a more informed and agile response to the COVID-19 pandemic but have also laid the groundwork for innovative solutions to future public health challenges [19].

The aim of the paper is to investigate the impact of the Russian full-scale invasion on the COVID-19 dynamics in Czech Republic using Prophet model.

2. Materials and Methods

This research advances a methodological framework designed to evaluate the repercussions of the Russian full-scale invasion of Ukraine on the epidemiological trends of infectious diseases. Initially, the approach entails crafting a predictive machine learning algorithm tailored to map the epidemic's trajectory within the chosen locale. Subsequently, the model's accuracy is ascertained by applying it to pre-invasion health data, specifically morbidity and mortality statistics associated with infectious diseases, collated from the 25th of January to the 23rd of February 2022.

Upon validation, the model projects the expected disease incidence and related fatalities within the initial thirty-day period following the onset of the Russian military invasion beginning on the 24th of February 2022. A comparative analysis examines the divergence between the model's projections and the health outcomes observed during the conflict.

Further, the study delves into dissecting the elements that impinge upon the progression of infectious diseases, considering the peculiarities of both the pathogen in question and the geographical setting. In the final phase of the methodology, a critical evaluation of the findings is conducted to unearth potential risks to the public health infrastructure. This comprehensive examination is pivotal for informing the strategic deployment of interventions to mitigate the propagation of infectious diseases amidst wartime conditions.

The Prophet model, developed by Facebook's Core Data Science team, is a decomposable time-series forecasting procedure for simulating COVID-19 dynamics, among other applications [21]. This model can be beneficial for public health officials to forecast the number of cases, hospitalizations, and other critical variables over time.

The underlying principle of the Prophet model is to decompose the time series into three main components: trend, seasonality, and holidays. It accommodates non-linear trends with daily, weekly, and yearly seasonality, plus holiday effects. It does this by fitting the following equation:

$$\mathrm{y(t)} = \mathrm{g(t)} + \mathrm{s(t)} + \mathrm{h(t)} + \epsilon_t, \tag{1}$$

where y(t) is the predicted value; g(t) represents the trend function, which models non-periodic changes; s(t) models periodic changes, such as seasonality; h(t) represents the effects of holidays which occur on potentially irregular schedules over one or more days; ϵ_t represents the error term which accounts for any unusual changes not accommodated by the model.

The trend component g(t) is typically modeled using a piecewise linear or logistic growth curve to handle different types of growth patterns in the data:

For linear growth:

$$g(\mathrm{t}) = \mathrm{kt} + \mathrm{m}, \tag{2}$$

For logistic growth:

$$g(\mathrm{t}) = \frac{C}{1 + e^{-k(t-m)}}, \tag{3}$$

where, k represents the growth rate, m dictates the offset parameter, and C is the carrying capacity (the maximum achievable point for the metric being forecasted, which is particularly relevant when forecasting something like an infection rate that has a natural cap).

Seasonality, s(t), is modeled using the Fourier series to provide a flexible model of periodic effects. Prophet relies on a yearly seasonal component using a Fourier series with P yearly seasonality, which is given by:

$$s(\mathrm{t}) = \sum_{n=1}^{N} (a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin(\frac{2\pi nt}{P})), \tag{4}$$

where N is the number of Fourier terms used to model the seasonality, and a_n, b_n are coefficients to be fitted.

Holiday effects, h(t), are included as an indicator function that equals 1 if the time t is a holiday 0 otherwise.

The error term ϵ_t generally assumes that these unpredictable effects are normally distributed.

The parameters for these models are fitted using historical data, and the model is then used to forecast future trends. The Prophet model's strength lies in its robustness to missing data and trend shifts, making it useful for scenarios such as COVID-19, where sudden changes in trend can occur due to lockdowns or other interventions [21].

For COVID-19 dynamics, this model can incorporate effects such as lockdowns or vaccination drives as holiday effects and accommodate sudden changes in the trend by adjusting the growth rate k. The flexibility to incorporate these features makes the Prophet model a powerful tool for public health forecasting and planning during the pandemic.

The Prophet model has been acknowledged for its intuitive parameters that are relatively simple for analysts to adjust. It facilitates an ease of use not always present in more complex forecasting algorithms. One of its significant advantages is the model's capacity to handle missing data and outliers, as well as to incorporate potentially influential events like holidays, which can be critical for predicting erratic behaviors in time-series data. Additionally, the model's robustness against shifts in trends and its ability to capture a wide range of seasonalities – weekly, monthly, or annually – render it particularly beneficial for long-term forecasting.

However, the Prophet model is not without its drawbacks. Its performance is heavily reliant on the quality and granularity of the input data; insufficient or overly aggregated data can substantially compromise its accuracy. Moreover, the model may fall short when dealing with highly volatile data series or non-standard frequencies not accounted for in its core structure. The simplistic assumption of independent holiday effects might also not hold in more complex scenarios where holidays interact with underlying trends. Finally, while Prophet excels in its simplicity and accessibility, it may not reach the sophistication required for capturing more intricate relationships within the data that advanced statistical or machine learning models might detect.

The model's hyperparameters, which are crucial for its predictive capacity, are outlined in Table 1.

Table 1
Model's hyperparameters

Hyperparameter	Cumulative cases	Cumulative deaths	New cases	New deaths
changepoint_prior_scale	0.24454911994868200	0.495943083231842	0.0162143017991519	0.0124262005764601
changepoint_range	0.9044859898296930	0.806987492979227	0.873637544093367	0.889988896728438
daily_seasonality	FALSE	TRUE	TRUE	FALSE
growth	Linear	Linear	Linear	Linear
seasonality_mode	Multiplicative	Additive	Additive	Additive
seasonality_prior_scale	0.00415986119232672	0.00579797001191652	0.116149503891177	0.00304460686463523
weekly_seasonality	TRUE	TRUE	FALSE	FALSE
yearly_seasonality	FALSE	FALSE	FALSE	TRUE

The table delineates the parameters for four different epidemiological measures: cumulative cases, cumulative deaths, new cases, and new deaths. For example, the changepoint_prior_scale, which governs the flexibility of the trend, is set to approximately 0.245 for cumulative cases and is higher at nearly 0.496 for cumulative deaths, suggesting a more responsive adjustment to changes for the latter. The changepoint_range, indicating the proportion of the history where trend changes are sought, varies across the measures but remains above 0.8, providing a broad window for detecting such changes.

Regarding seasonality, daily_seasonality is enabled only for cumulative deaths and new cases, implying that daily fluctuations are significant for these measures. The growth parameter is consistent 'Linear' across all measures, indicating a linear trend assumption in the model's structure. The seasonality_mode differs; 'Multiplicative' is used for cumulative cases, whereas 'Additive' is preferred for the other measures, reflecting different approaches to how seasonality impacts the trend.

Seasonality_prior_scale, which sets the importance of seasonal components, is notably low for cumulative cases and new deaths, suggesting a conservative approach to fitting seasonal effects. Weekly_seasonality is applied to cumulative cases and deaths, which could capture weekly patterns like reporting fluctuations. Conversely, yearly_seasonality is considered only for new deaths, potentially to account for long-term seasonal effects such as weather changes or systematic variations in mortality reporting.

3. Results

Utilizing the Python programming environment, the Prophet model was deployed to evaluate and refine its predictive performance regarding the COVID-19 pandemic's trend. The model's forecasting accuracy was methodically examined across time horizons of three to thirty days. For validation, this study utilized COVID-19 incidence and mortality statistics for the Czech Republic, procured from the World Health Organization's COVID-19 Dashboard [22]. The data set for assessment included daily reported cases and fatalities attributed to COVID-19 within the Czech Republic, covering the period from the 25th of January to the 23rd of February 2022. This interval reflects the initial 30 days after the beginning of the full-scale Russian invasion of Ukraine.

Figure 1 shows the results of forecasting of the COVID-19 cumulative cases in Czech Republic from 25 January, 2022 to 23 February, 2022.

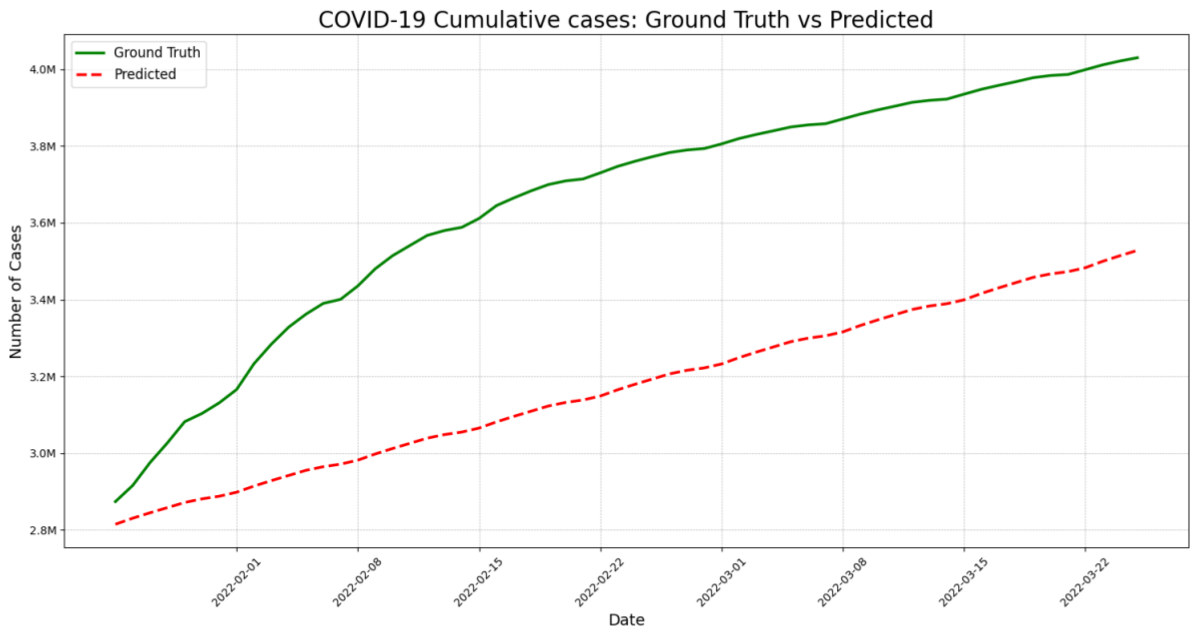

Figure 1: Forecast of the COVID-19 cumulative cases in Czech Republic (25.01.22 – 23.02.22)

Figure 2 shows the results of forecasting of the COVID-19 cumulative deaths in Czech Republic from 25 January, 2022 to 23 February, 2022.

To evaluate the performance of the model we have used the Mean Absolute Percentage Error (MAPE). MAPE is a statistical measure used to assess the accuracy of a forecasting model [23]. It quantifies the average magnitude of errors as a percentage, providing a clear representation of the forecast accuracy in relative terms. This is calculated by taking the mean of the absolute values of the individual percentage errors between the forecasted and actual values. MAPE is particularly useful as it offers a straightforward interpretability of the forecast precision, with lower values indicating higher accuracy. However, its effectiveness may be limited when dealing with data points close to zero, as the percentage error can become disproportionately high.

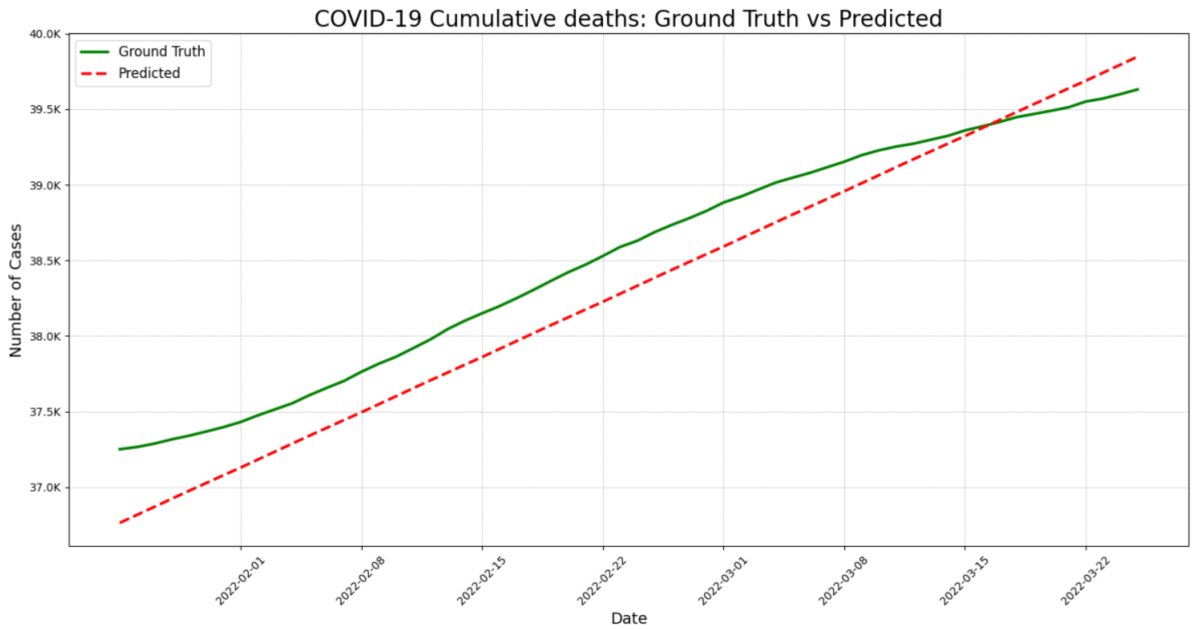

Figure 2: Forecast of the COVID-19 cumulative deaths in Czech Republic (25.01.22 – 23.02.22)

Table 2 shows MAPE for cumulative data forecast from 25 January, 2022 to 23 February, 2022.

Table 2
MAPE of the cumulative data forecast (25.01.22 – 23.02.22)

Period of the forecast (days)	Infected	Dead
3 days	3,24%	1,23%
7 days	5,58%	1,07%
14 days	9,08%	0,91%
21 days	11,63%	0,85%
30 days	13,64%	0,82%

The MAPE values for the infected category show an increasing trend as the forecast period lengthens, starting from 3.24% for the 3-day forecast and rising to 13.64% for the 30-day forecast. This increment suggests that the model's predictive accuracy decreases as the forecasting horizon extends. In contrast, the MAPE for the dead category decreases slightly over more extended forecast periods, starting from 1.23% at 3 days and reducing to 0.82% at 30 days, indicating a relatively consistent and better forecasting performance for cumulative deaths compared to infections over the given period.

Forecasts were calculated to examine the dynamics of the COVID-19 epidemic within the Czech Republic from 24 February, 2022 through 25 March, 2022. This interval marks the first month after the beginning of the full-scale Russian invasion of Ukraine.

Figure 3 shows the results of forecasting of the COVID-19 cumulative cases in Czech Republic from 24 February, 2022 to 25 March, 2022.

Figure 4 shows the results of forecasting of the COVID-19 cumulative deaths in Czech Republic from 24 February, 2022 to 25 March, 2022.

Table 3 shows MAPE for cumulative data forecast from 24 February, 2022 to 25 March, 2022.

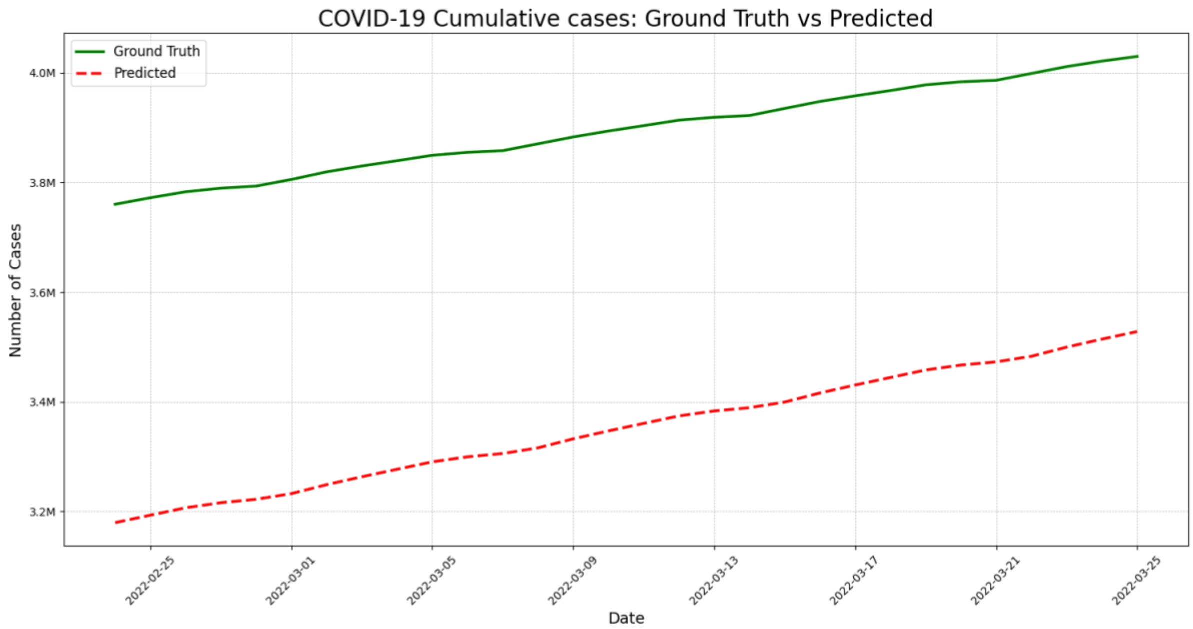

Figure 3: Forecast of the COVID-19 cumulative cases in Czech Republic (24.02.22 – 25.03.22)

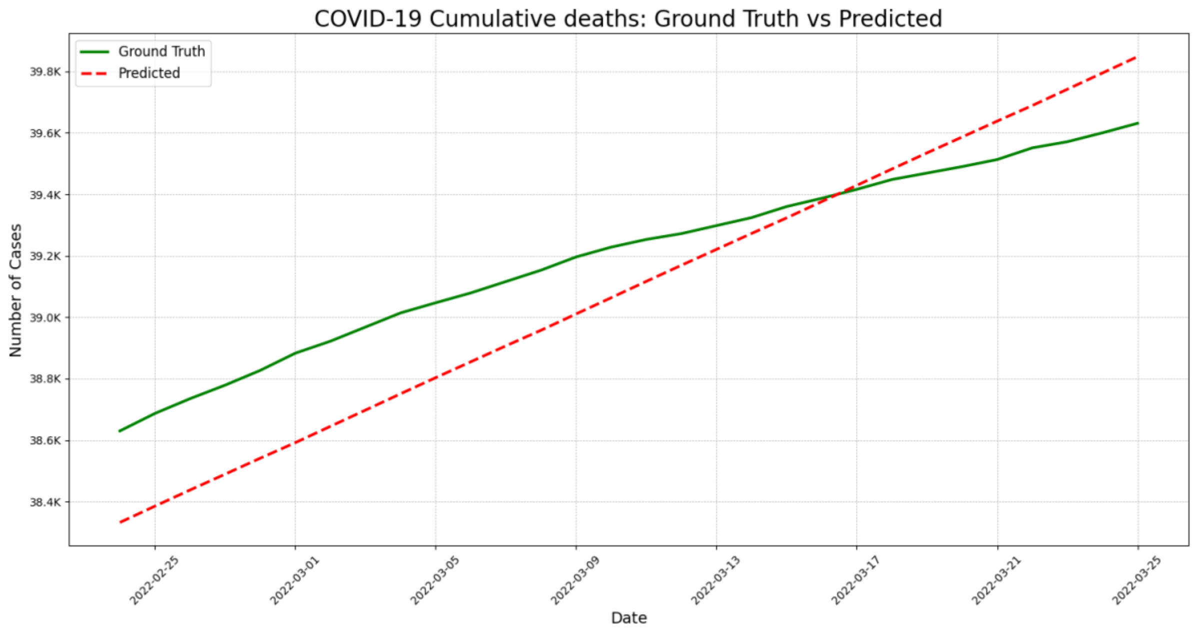

Figure 4: Forecast of the COVID-19 cumulative deaths in Czech Republic (24.02.22 – 25.03.22)

Table 3
MAPE of the cumulative data forecast (24.02.22 – 25.03.22)

Period of the forecast (days)	Infected	Dead
3 days	18,12%	0,78%
7 days	17,89%	0,76%
14 days	17,39%	0,67%
21 days	16,89%	0,52%
30 days	16,27%	0,45%

Throughout forecast periods extending from 3 to 30 days, the MAPE for the infected category starts at 18.12% for the 3-day forecast and demonstrates a downward trend, decreasing to

16.27% for the 30-day forecast. This indicates a gradual improvement in the model's predictive accuracy over time for forecasting infections. Similarly, the MAPE for the dead category shows a consistent decrease from 0.78% at the 3-day forecast to 0.45% at the 30-day forecast, suggesting a sustained enhancement in the precision of death forecasts as the forecast period lengthens.

4. Discussion

In the discussion of the interplay between the COVID-19 pandemic dynamics and significant sociopolitical events, particularly the full-scale Russian invasion of Ukraine, several critical insights emerge. This paper has engaged with the multifaceted repercussions of the conflict on public health, primarily through the lens of infectious disease spread and management. The empirical data gathered and forecasted via the Prophet model illustrate notable deviations in the infection and mortality rates from the predicted trajectories post-invasion, underscoring the profound impact of war on healthcare systems and disease control measures.

The observed decline in the accuracy of the cumulative case forecasts for the period following the Russian full-scale invasion of Ukraine (24.02.22 - 25.03.22) suggests that the epidemiological dynamics of COVID-19 in the Czech Republic were significantly altered during this time. This decrement in predictive accuracy could be attributable to a myriad of factors induced by the conflict, including but not limited to disruptions in routine healthcare practices, alterations in population behavior due to the crisis, and the challenges in maintaining rigorous disease surveillance and reporting amidst socio-political turmoil.

Conversely, the improvement in forecast accuracy regarding cumulative deaths within the same timeframe offers a paradoxical narrative. It implies that, despite the upheaval caused by the invasion and its impact on the health system's efficacy in tracking and managing COVID-19 cases, the prediction of fatal outcomes became more precise. This increased accuracy could be indicative of several scenarios. One possibility is that the data reporting for mortality could have become more consistent or accurate despite the conflict. Another perspective might suggest that while case numbers were subject to more significant fluctuation due to the reasons mentioned above, the fatality rate may have followed a more predictable pattern, potentially due to improved treatment protocols or a stable or decreasing virulence of the prevalent COVID-19 variants.

In the extended discussion of these outcomes, it is critical to integrate a nuanced understanding of how the chaos of war can ripple through the public health infrastructure, influencing not just the spread of infectious diseases but also the mechanisms of data collection and analysis. The increase in predictive accuracy for cumulative deaths, despite the invasion, may reflect a complex interplay of factors, including potentially more focused medical attention to severe COVID-19 cases or an artifact of data prioritization that inherently occurs in crisis settings.

This dichotomy between case and death predictions highlights the complexity of epidemiological modeling in the context of significant social disruptions. It further reinforces the need for dynamic modeling approaches sensitive to rapid changes in public health landscapes. The insights gained from analyzing these predictive discrepancies underscore the importance of continuous model refinement and the incorporation of real-time data to inform public health strategies, particularly in settings of socio-political instability.

The disruption of healthcare services due to the war cannot be overstated. It precipitated a notable decline in routine medical care, vaccination efforts, and a reorientation of health resources towards emergent war-related injuries and traumas. Consequently, the diversion of medical resources has been paralleled by increased COVID-19 transmission risks, mainly due to population displacements and the congregation of individuals in shelters devoid of appropriate sanitary conditions.

Moreover, assessing machine learning models, like Prophet, in forecasting the pandemic's trajectory has yielded insights into the necessity and utility of adaptable and robust predictive tools in public health. Despite their utility, these models face limitations, especially when external variables such as social upheaval are introduced. The forecast errors, represented by MAPE, indicate variability in predictive accuracy, which tends to be more pronounced over extended forecast periods. Nonetheless, it is imperative to acknowledge that forecasting models are indispensable for early intervention strategies and resource allocation in public health crises.

Migration patterns in response to the invasion have also significantly affected the COVID-19 pandemic's landscape. The influx of refugees into neighboring countries like the Czech Republic has introduced new challenges for public health surveillance and infrastructure. The movement of large populations across borders during a pandemic can exacerbate the spread of the virus, overwhelming local healthcare systems and complicating containment and mitigation efforts.

In reflecting upon these phenomena, it is evident that an integrative approach to public health planning is essential - one that considers epidemiological trends in the context of geopolitical and societal shifts. The pandemic's trajectory cannot be fully understood nor anticipated without accounting for such extrinsic factors. Furthermore, the observed data underline the critical need for international cooperation and support, significantly when national healthcare systems are compromised due to factors like armed conflict.

Examining the cumulative data forecasts, particularly the MAPE across different timeframes, further solidifies the argument that disease forecasting in societal upheaval requires models to incorporate real-time changes in social behavior and healthcare access. While the model displayed a decreasing trend in predictive error for cumulative deaths, indicating an improvement over time, this could also reflect the adaptation of healthcare systems to crisis conditions or changes in reporting accuracy under duress.

In summary, the interrelation between a global pandemic and an unanticipated military conflict has revealed the complexities of managing public health in the contemporary world. The experience underlines the importance of resilient health systems, the adaptability of predictive models, and the need for comprehensive health policies to withstand the pressures of unforeseen global events.

5. Conclusions

In conclusion, the study's findings delineate the multifaceted impact of the Russian invasion of Ukraine on the epidemiological trajectory of COVID-19 within the Czech Republic. The decreased precision in forecasting cumulative COVID-19 cases post-invasion underscores the profound effect geopolitical instability can have on disease surveillance and prediction. It is indicative of the myriad ways in which conflict can disrupt healthcare systems and the collation and reliability of epidemiological data.

In contrast, the improved accuracy in predicting COVID-19-related mortality during the same period presents an intriguing counterpoint, suggesting a differential effect of the conflict on various aspects of the pandemic's progression. This improvement could reflect an unanticipated standardization in mortality data reporting or a proper stabilization in mortality trends despite the chaos of the surrounding circumstances.

These results illuminate the complexities of public health monitoring in times of crisis and the crucial role that accurate, timely data plays in pandemic response efforts. They highlight the resilience of mortality data amidst disruptions and underscore the potential need for augmented predictive modeling techniques that can better account for the unexpected variability introduced by such external factors.

Ultimately, this study emphasizes the need for robust, adaptable public health infrastructure to maintain surveillance and care delivery during geopolitical crises. It also calls for international collaboration in data sharing and model development to enhance preparedness and response strategies in the face of concurrent public health and political emergencies. The profound implications of these findings advocate for a reinforced global commitment to public health as an integral component of national security and stability.

The scientific novelty of this research resides in its analytical approach, integrating geopolitical events into epidemiological predictive models. By capturing the influence of the Russian invasion of Ukraine, the study provides a novel empirical understanding of how such crises can perturb disease transmission dynamics and forecasting. It extends current epidemiological forecasting methodologies by introducing conflict parameters, thus offering a more nuanced model sensitive to sudden sociopolitical shifts, bridging the gap between public health research and political science.

On the practical front, the research introduces a new paradigm in public health surveillance by accounting for the impact of military conflict on infectious disease progression. The enhanced model is a tool for policymakers and healthcare providers, allowing for more informed decision-making in crisis conditions. This approach enables a dynamic adjustment of health resources and responses in real time, potentially mitigating the adverse effects of conflicts on the spread of infectious diseases. The practicality of this model lies in its adaptability, providing a template for how health systems can maintain operational integrity amidst the chaos of war or other disruptions.

Future research should refine these models to include a broader spectrum of sociopolitical disruptions, such as economic sanctions, natural disasters, or large-scale migration. Expanding the data set to global incidences can enrich the model's predictive power and application across different contexts. Further exploration into machine learning and artificial intelligence could enhance the model's ability to learn from complex and non-linear data, providing more accurate forecasts in the face of uncertainty. Moreover, interdisciplinary collaboration will be essential, integrating insights from epidemiology, political science, and data science to bolster the model's robustness and utility in anticipating public health needs during global crises.

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