



Article

Simulation of the Progression of the COVID-19 Outbreak in Northwest Syria Using a Basic and Adjusted SIR Model

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Abstract: Syria has experienced armed conflict since 2011, and the provision of health care has been severely compromised due to the hostilities. At the time of writing, Northwest Syria (NWS) was outside governmental control and faced the challenges of the COVID-19 outbreak. Since the emergence of this disease, several studies have looked at the dynamics of COVID-19 transmission, predicted its progression, and determined the impact of different preventive measures. While most of these studies' settings were in stable contexts, this study investigated the progression of the COVID-19 pandemic in Northwest Syria, a conflict-affected region, for nine months (from July 2020 to March 2021) using the Suspected-Infected-Removed (SIR) model. We adjusted the SIR model to study the impact of wearing facial masks on the outbreak dynamics and progression. Based on available data and using the basic and adjusted SIR models, we estimated the value of the basic reproduction number (R_0), which provides an initial prediction of disease progression. Using the basic SIR model, the estimated R_0 for the first wave of SARS-CoV-2 in Northwest Syria was 2.38. The resulting figures were overestimated in comparison with the reported numbers and data on the COVID-19 pandemic. However, the results were significantly reasonable when we adjusted the model for a preventive measure (in this case, wearing face masks). Face masks, the most available preventive measure to be applied in emergency and conflict settings, remarkably affect the outbreak dynamics and may play a key role in controlling and limiting the spread of COVID-19. The novelty of the study is provided by simulating the progress of the COVID-19 outbreak in conflict settings, as it is the first study to predict the dynamics of COVID-19 disease in NWS by adjusting for face-mask-wearing as a preventive measure to explore its impact on outbreak dynamics.

Keywords: COVID-19; SARS-CoV-2; coronavirus; SIR model; outbreak; Northwest Syria; emergency; conflict; humanitarian; face mask



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1. Introduction

Since late 2019, the world has been facing the rapid spread of a novel viral infection, coronavirus disease 2019 (COVID-19), caused by a new strain of coronavirus, i.e., severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The World Health Organization (WHO) declared a global pandemic on 11 March 2020 [1]. Due to the fact that it has been designated the sixth international public health emergency of concern, the COVID-19 pandemic is considered a public health threat [2]. COVID-19 has become a highly active study domain, with topics such as transmission dynamics and patterns, preventative methods, and risk factors all being explored in depth [3]. At the time of writing this paper, preventive measures were the available strategy to control the spread of the disease. This includes improved hygiene, social distancing, wearing face masks, and home health care programs [4–6]. The significant risk of COVID-19 is related to the high transmission rate of the virus, which spreads via respiratory droplets and aerosols [7]. SARS-CoV-2 has been described as highly contagious, as it is two to three times more contagious than

influenza, and infected individuals, even if they are asymptomatic, can transmit the disease to susceptible individuals [8].

The ability to simulate the transmission dynamics of epidemics over time is critical because it allows researchers to have a better understanding of the epidemiological situation and the efficiency of control measures [9]. Mathematical modeling is a practical approach for simulating the epidemic curve and disease progression and estimating the number of infected cases [10]. In addition, public understanding and policy legislation depend on the data determined by epidemic progression models that can be interpreted as actionable policies [11]. Multiple mathematical models have been used in the literature to understand the epidemiological characteristics of pandemics [12]. The most common approach to predict epidemic development is the basic SIR model, which is a compartmental model of susceptible (S), infectious (I), and removed (recovered and death) (R) cases. This model is composed of a system of differential equations used to predict the dynamics of an epidemic based on predefined parameters, such as transmission and removal rates [13]. The transmission rate of the disease is high compared with other types of coronaviruses [14].

The first COVID-19 cases in Northwest Syria (NWS) were reported in July 2020 [15]. NWS refers to the geographical areas (parts of the Aleppo and Idlib governorates) controlled by opposition armed groups [16]. It is estimated that more than three million people are in the Idlib governorate, about 1.5 million of whom are internally displaced persons (IDPs). As a result of the deterioration of humanitarian conditions, displacement, and collapse of the health system and health governance, the resilience of 4.1 million people living in NWS has been eroded by the prolonged crisis [17,18]. The health system in NWS has suffered enormous challenges during the conflict. Many factors weaken the capacities of the system, such as the presence of millions of IDPs, overcrowding, and poverty [19].

With the high density of IDPs in camps, economic collapse, and the lack of financial and human resources, many experts and researchers have predicted an increased transmission risk of COVID-19 disease, resulting in catastrophic figures overwhelming the ramshackle humanitarian situation in NWS [20]. The COVID-19 outbreak poses serious challenges in NWS due to its fragile health system and economic and social collapse [21,22]. Moreover, the crowded settlement settings and unhygienic conditions make it impossible to adhere to preventive measures and precautions [23]. Multiple surveys have been carried out in NWS to understand people's perspectives on preventive measures. These surveys showed that face masks are more affordable and viable than other preventive measures [24]. Mask-wearing in NWS was estimated to be among the most used preventive measures [25].

In the paper, we analyze the progression of COVID-19 disease in a war-affected area, NWS, for 9 months (from 15 July 2020, when the first confirmed COVID-19 cases in NWS were reported [26], until 31 March 2021) using SIR models. After estimating the transmission and removal rates of the COVID-19 outbreak in NWS using differential equations, this study provided a comprehensive understanding of the progression of the outbreak. Moreover, the SIR model was adjusted by the factor of wearing face masks to study its impact on the outbreak dynamics, thereby contributing to the literature on simulating the dynamics of the COVID-19 pandemic, particularly in a conflict-affected setting (Syria).

2. Materials and Methods

At the time of writing this research, the number of confirmed COVID-19 cases and deaths was drastically increasing globally [26]. The present study is based on COVID-19 time-dependent incidence data from the beginning of the outbreak in NWS on 15 July 2020 to 6 September 2021. COVID-19 data for NWS were taken from repositories maintained by the WHO [27], which is specific for the NWS COVID-19 outbreak. At the time of writing this study, the total number of people in NWS was $N = 4.1$ million [18]. The epi curve and number of cases are available on the dashboard. Data were extracted from the dashboard to an Excel sheet and SPSS software program, where the equations and calculations were performed.

2.1. Differential Equation and Basic SIR Model

The SIR epidemic disease model of Kermack and McKendrick was utilized in this study to predict and assess the spread of the COVID-19 outbreak in NWS by applying ordinary differential equations (ODE) [28]:

$$d(S) = -\beta SI \quad (1)$$

$$d(I) = \beta SI - \gamma I \quad (2)$$

$$d(R) = \gamma I \quad (3)$$

Based on the SIR epidemic model, the population consisted of three groups: suspected, infected, and removals. We denote the sizes of these subpopulations at time t by S , I , and R , where:

$d(S)$, $d(I)$, and $d(R)$ refer to changes in the susceptible, exposed, and removed cases over time, respectively;

β is the transmission rate constant;

γ is the removal rate constant.

Equations (1)–(3) represent the changes in the sizes of S , I , and R over time. The sum of S , I , and R is the total population. Several assumptions were considered to determine the values of the parameters of the ODE. The first assumption is that the NWS population N remains constant, and non-COVID-19-related deaths and new births are not counted throughout the study timeframe. This assumption indicates that

$$N = S + I + R \quad (4)$$

Therefore, the sum of changes in the three groups over time is 0.

$$d(S) + d(I) + d(R) = 0 \quad (5)$$

The second assumption is that the rate of increase in I is due to the contact between I and S . The increase rate is constant and is referred to as β ($\beta > 0$), which is the infection coefficient. The third assumption is related to the removal coefficient γ ($\gamma > 0$), which is constant and refers to the rate of recovery and death. We also assumed that everyone who recovers would gain long-lasting immunity and no longer be susceptible to the disease. Moreover, we did not consider the impact of preventative measures in NWS on the basic SIR model or outbreak progress. However, later in this study, we adjusted the model based on the use of face masks and figures related to this preventive measure in NWS to explore its impact on the outbreak progress.

As a result of Equations (1)–(3), and to measure the changes in S , I , and R over time, it could be said that the change in S at time $t + 1$ is equal to the value of S until time t , excluding those who became infected at time t . From Equation (1):

$$d(S)_{t+1} = S_t - (\beta \times S_t \times I_t) \quad (6)$$

The change in the number of infected people I at the time $t + 1$ equals the value of I until the time t , plus those who moved from S to I , minus those who died or recovered (R group). From Equations (1), (2) and (6):

$$d(I)_{t+1} = I_t + (\beta \times S_t \times I_t) - \gamma I_t \quad (7)$$

The removed cases at time $t + 1$ represent those who died and recovered until the time t , plus those who died or recovered at the time t . From Equations (1), (3) and (7):

$$d(R)_{t+1} = R_t + \gamma I_t \quad (8)$$

S_0 refers to the number of susceptible cases at the initial phase of the outbreak. In the context of COVID-19, the entire population is susceptible to the virus at the initial phase without extrinsic factors such as immunization or lockdown. Thus, $S_0 = N$ [29].

Using the available data from the NWS dashboard for COVID-19, we estimated the value of β and γ using the ODE.

2.2. The Basic Reproduction R_0 and Effective Reproduction R_e Numbers

The reproduction number R is a key epidemiological parameter to estimate the average number of newly infected individuals from a single infected case. At the initial stage of the outbreak, when it emerges in an entirely susceptible population, R is referred to as the basic reproduction number, R_0 . Throughout the time, the reproduction number is referred to as the effective reproduction number, R_e . These parameters provide valuable information about the potential spread of an infection in a population and the characters of the outbreak wave [30]. In other words, if a person has a particular disease, then the reproduction number gives the number of infections, on average, that the person will cause, or how many individuals that person will infect, within the population [31]. The severity of an epidemic at its initial phase can be summarized as follows:

$R_0 > 1$: The epidemic exponentially increases. In other words, one infected individual infects more than one individual on average.

$R_0 \leq 1$: The epidemic will not occur, and the disease will die out without affecting a large portion of the population [32].

Simulating the dynamics of an epidemic through a specific period can be achieved by estimating the effective reproduction number, R_e . The effective reproduction number is the average number of secondary infections caused by one infection during the same period. R_e is a variable number that shows time-dependent variation due to the decline in susceptible subjects and the implementation of preventive and control measures. The pandemic increases exponentially, and a wave (sudden increase in cases) is expected, as long as the value of R_e is >1 . In contrast, when R_e is <1 , the epidemic is dying out. The maximum value of R within a specific period represents the wave peak [33].

For the SIR model, the value of R_0 is calculated based on Equation (9):

$$R_0 = \beta D = \beta / \gamma \quad (9)$$

D is the average duration of infection, and $D = 1/\gamma$. Thus,

$$\gamma = 1/D \quad (10)$$

$$\beta = \tau c \quad (11)$$

τ is the transmissibility rate of the disease, i.e., the probability of transmitting the disease. $\tau = 2.6$ [34].

c is the contact rate.

In other words, the transmission rate β is related to the infector's contact rate with susceptible subjects and the probability of transmitting the disease to them [31].

The equation of the effective reproductive number is [35]:

$$R_e = (S_t \times R_0)/N \quad (12)$$

where $S_0/N = 1$ at the initial stage of the outbreak.

3. Results

3.1. Estimating the Basic Reproductive Numbers without Control Measures

The next step to simulate the progression of COVID-19 is to determine the parameters β and γ that best describe the current evolution of the disease. The estimation was imitated through the ODE and by applying the basic SIR model to predict the variation in the differential equation parameters.

COVID-19 recovery speed is best determined from a WHO study that examined more than 55,000 cases in China at the beginning of the outbreak globally. The study revealed that for mild illness, the time from the onset of symptoms to recovery is, on average, 14 days for mild cases ($D = 14$ days) and 6–8 weeks for severe infections [36]. Therefore, it could be said that the removal rate $\gamma = 1/D = 1/14 = 0.071$.

In the absence of comprehensive data and studies about the contact rate and COVID-19 dynamics and transmissions in NWS, we had to calculate the value of β based on its definition: “ β refers to the probability of infection to be transmitted or the transmissibility rate multiplied by the contact rate which is the average number of people the infector has contacted with (Equation (11))”. In this study, we looked at confirmed cases due to infector-infectee contact based on data shared by EWARN in NWS during the period from 15 July 2020, when the first confirmed cases were recorded, i.e., $I_0 = 10$ (based on the COVID-19 dashboard), until 22 September 2020. Considering the value of $\tau = 2.6$, and identifying the contact rate per case and the number of infectees per infector, we estimated the value of β to be 0.17 (min = 0.04–max = 0.28, standard deviation (SD) = 0.05, confidence interval (CI): 95%). As a result, the value of $R_0 = \beta/\gamma \approx 2.38$. The SIR model based on the values of β , γ , and R_0 is illustrated in Figure 1. From Equation (2), and based on available data, it was found that the sum of infected cases during the period of the study exceeds 3 million people, which is overestimated compared to available figures on the number of infected cases on the dashboard.

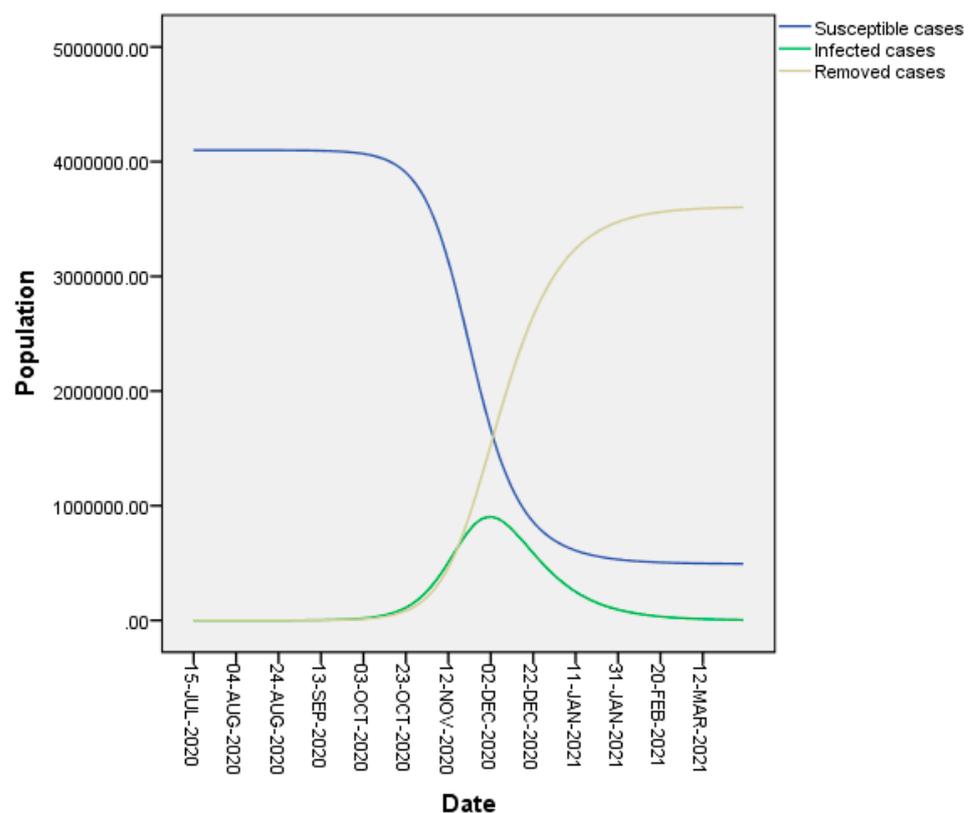


Figure 1. Progression of the COVID-19 outbreak in NWS from July 2020 to March 2021 based on the SIR model.

3.2. The Impact of Using Face Masks on the Basic Reproduction Number

COVID-19 has a high infectivity rate. Transmission via droplets of saliva or discharge from the nose is the primary mode of direct transmission [37]. To control the spread of the virus, it is imperative to reduce human-to-human contact, disinfect day-to-day objects, and maintain proper self-hygiene (washing hands regularly, proper coughing and sneezing techniques, social distancing, and the use of face masks) [38]. In this study, we addressed the

impact of using face masks on the reproduction number and outbreak dynamics ($R0a$: the adjusted value of $R0$ due to the factor of wearing face masks). Other preventive measures were not considered in this study because of the lack of evidence on these measures from NWS. Adhering to preventive measures such as lockdown, quarantine, isolation, and social distancing is not common among people in the context of NWS, where the majority of them are IDPs who live in crowded camps with limited sources of income. The deteriorated socio-economic status and absence of governmental structure to impose preventive measures make it difficult for people to adhere to the lockdown and social distancing rules [15]. According to the WHO, using face masks is one of the few COVID-19 preventive measures viable and available for refugees and IDPs in camp settings [39].

In an evidence review study, it was found that wearing masks reduces the reproduction number by a factor

$$\delta = (1 - e \times p_m)^2 \quad (13)$$

where e is the efficacy of trapping viral particles inside the mask, and p_m is the percentage of the population that wears masks [40]. Thus, it can be concluded that

$$R0a = R0 \times \delta \quad (14)$$

Studies addressing the efficiency of preventive measures to COVID-19 are still scarce [41]. The filtration efficiency reflects the mask's ability to filter particulates and microorganisms, with a cut-off point of $0.072 \mu\text{m}$ [42], assuming that the size of SARS-CoV-2 is 0.07 to $0.09 \mu\text{m}$ [43]. In NWS, cloth masks were the most available due to the shortage of other types of masks in the market. Anecdotal evidence supports the widespread personal use of cloth masks [44,45]. Therefore, fabric mask performance was evaluated in this study based on their filtration efficiency. To estimate the value of e , we have reviewed many studies about face masks and their efficacy in reducing COVID-19 transmission [46–50]. We estimated the value of e from studies of low risk of bias which studied cloth masks similar to face masks available and used in NWS. The average value of e of the fabric mask was $e = 0.2$ [42,47]. According to an assessment released by REACH in NWS during the time of the study, about 30% of the population use face masks ($p_m = 0.3$) [51]. From Equation (13), and based on the estimation of P_m and e parameters, it could be said that $\delta = 0.88$. From Equation (14), $R0a$ at the initial phase of the outbreak will decline from 2.38 to 2.1. Assuming that adherence to face masks is constant and started at the beginning of the epidemic, recalling Equation (9), $\beta = R0 \times \gamma$. By replacing the value of the adjusted basic reproduction number, we found that $\beta a \approx 0.15$ (βa is the adjusted transmission rate due to the factor of wearing face masks). Based on the adjusted values of $R0a$ and βa , the progression of the outbreak in NWS was simulated, as shown in Figure 2. From Equation (2), and using the adjusted value βa , it was found that the total number of infected cases from 15 July 2020 until March 2021 is 400257, which is more realistic when compared to the number of people and the actual outbreak dynamics and figures. Based on the values of $R0$ and $R0a$, the peak of the COVID-19 epidemic curve in NWS was estimated to be on 25 November 2020.

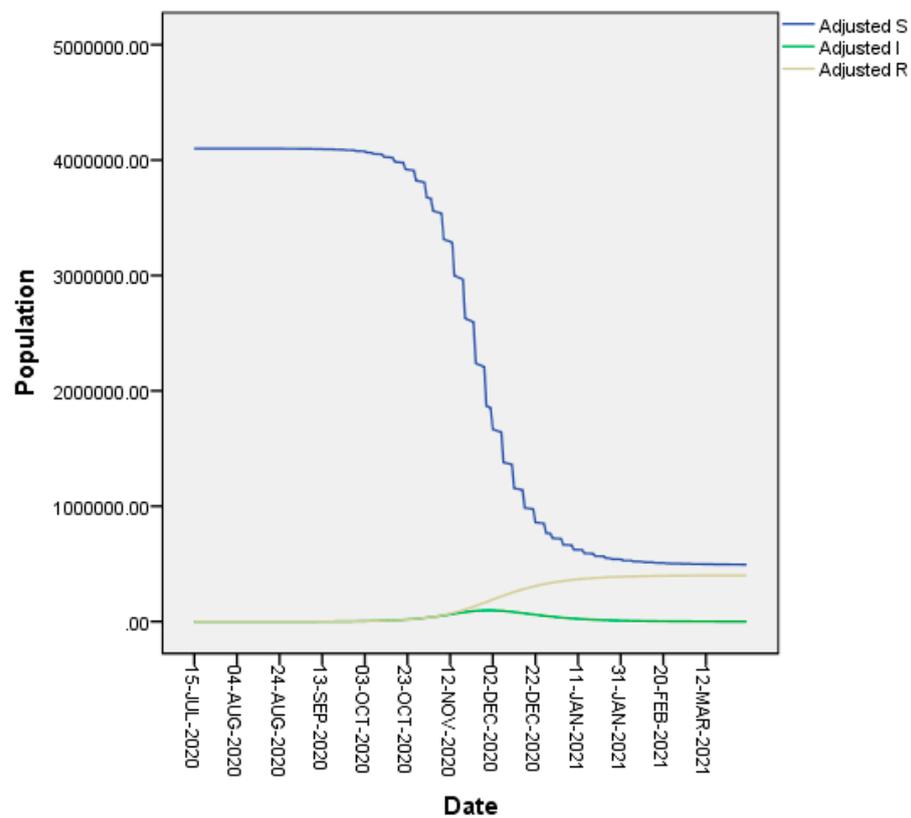


Figure 2. Progression of the COVID-19 outbreak in NWS from July 2020 to March 2021 based on the adjusted SIR model ($R_0a = 2.1$).

4. Discussion

Identifying the dynamics of outbreaks in conflict zones is difficult for a variety of reasons, including a lack of data and the absence of a comprehensive health information system. Observing how infectious diseases propagate and negatively impact society in fragile and war-affected states and conflict zones, on the other hand, provides us with a high-level epidemiological understanding that can be applied in real-world situations. The ability to model epidemics in a variety of situations and compare them to previously known environments enables better prediction of future outbreaks as well as the estimation of the effect of specific factors determining their spread rates and patterns, among other things.

This research is one of the few studies aimed at simulating the progression of the COVID-19 outbreak in a war-affected region of NWS using the basic and adjusted SIR models. The aspect of wearing face masks was applied in the adjusted SIR model to understand the impact of a preventive measure on the disease dynamics. According to the research findings, adjusting the SIR model by the factor of preventive measures results in more realistic and feasible data. The first case of SARS-CoV-2 in NWS was confirmed in July 2020 [20]. In this study, the progress of the COVID-19 pandemic in NWS was investigated to reveal its epidemiological characteristics in a region (Syria) that has been affected by a humanitarian and political crisis for a prolonged time.

The setup used in this study bears a close resemblance to many other approaches that highlight COVID-19 dynamics. Nonetheless, the methodology of this research appraises one of the most widely followed preventive measures (face mask use), which would significantly change the spread and development of the disease. Based on this, the SIR model for NWS was customized and put forward. This research generates noteworthy interest in terms of outbreak simulation methods by tailoring the SIR model to a confounding factor.

Preventive measures such as wearing face masks, lockdowns, and social distancing reduce both transmissibility and contact rates, which will consequently reduce the values of β , R_e , and R_0 . The higher the value of R_0 , the more severe the impact of the pandemic

(based on the SIR model) [52]. In the initial phase of the pandemic, the value of R_0 in NWS was 2.38.

We summarized the value of R_0 in several reviewed research studies in Appendix A. The mean R_0 value across the 34 reviewed studies was 3.2, and the median was 2.97. Figure 3 shows a boxplot of 77 values of R_0 according to the studies we reviewed from several countries.

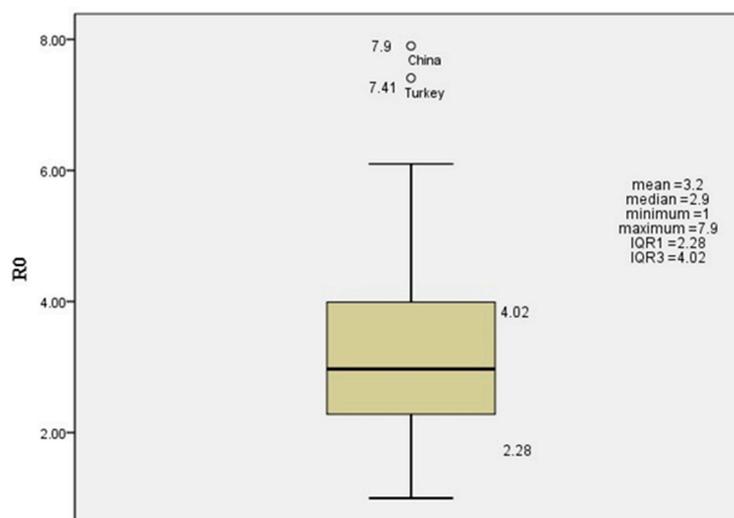


Figure 3. A boxplot of 77 values of R_0 according to the basic SIR model from different countries.

The value of R_0 in our study was within the interquartile range (IQR) of the boxplot, which is not unexpected because the methodology of these studies is similar to our study. However, the value of R_0a in this study was below the first IQR.

Of the total reviewed studies, only two presented the value of R_0 in Syria without any further political or humanitarian determinations [53,54]. The values of R_0 in these studies were 2.79 and 3.99, which are remarkably higher than the R_0 and R_0a values in this study (2.38 and 2.1, respectively).

There is a significant difference between the outputs of the basic SIR model and the adjusted SIR model. The preliminary results from the adjusted SIR model appear acceptable and realistic; the results from the SIR model, on the other hand, appear overstated and exaggerated when compared with actual figures and the total population of NWS. This conclusion can be supported by the facts and observations already collected and reported by humanitarian organizations in the Northwest Territories. 25 November 2020 was expected to be the day when the peak would occur in both models. A webinar hosted by John Hopkins University lecturers in October 2020 came to the conclusion that many studies and assessments have exaggerated and overestimated the spread of COVID-19, as well as its impact in humanitarian contexts. The results of the adjusted model support this conclusion [55].

The research findings were compared to studies from other contexts by validating the value of R_0 in NWS with different contexts and areas (Appendix A). This study is the first to investigate COVID-19 dynamics in NWS. Carrying out more studies in the region is of high importance to enrich the scientific literature on COVID-19 epidemiological characters in emergency settings and influence prevention and response strategies. Additionally, it goes without saying that in emergency settings where the health information system is collapsed, the reliability of available data imposes limits upon the quality of information and outcomes.

This research is one of the few studies that have discussed the COVID-19 outbreak dynamics in a conflict-affected area using the SIR model. While many studies have researched COVID-19 progression simulation using the SIR model, not all of them have addressed preventive measures and their influence on disease dynamics and development.

Furthermore, the research findings could be evidence to review the outbreak response modalities in emergency contexts where limited resources and risk communication and community engagement are challenging issues.

5. Conclusions

In this article, the progression of the first wave of the COVID-19 outbreak in NWS was predicted using the SIR model. In this study, we adjusted the prediction model parameters by adjusting for the factor of wearing face masks to investigate the effect of face masks as one of the most used and affordable preventive tools in NWS. Based on the research findings, the peak of the first wave was anticipated to occur on 25 November 2020, which is about 10 days after the actual peak, according to the epi curve on the NWS COVID-19 dashboard. The results of simulating the progression of the COVID-19 outbreak based on R_0 without considering the impact of preventive measures might lead to overestimating the number of infected cases. However, adjusting the SIR model by the factor of wearing face masks resulted in more reliable and feasible figures. In addition, it was found that wearing face masks has a decisive role in reducing the transmission rate, minimizing the number of infected people, and mitigating the impact of the outbreak. The research adds information on applying the SIR model after considering the preventive measure of wearing face masks, which is the most viable and applicable measure in emergency settings. Our findings suggest that it is recommended that humanitarian organizations and agencies in NWS develop advanced prevention strategies that take into account the applicable preventive measures, such as face masks, to reduce and control the disease's transmission rate, and thus, the impact of the outbreak.

The findings of this study have to be seen in the light of some limitations, such as the absence of a comprehensive health information system and consequently the lack of data, which made investigating the influence of other prevention methods on the disease progression impractical. There is no emergency-specific methodology to measure the impact of other factors, such as displacement and access to medical services, on the outbreak dynamics. However, these facts, on the other hand, underscore the importance of more epidemiological studies in emergency zones to understand the outbreak dynamics and the effectiveness of prevention and control strategies.

Author Contributions: Conceptualization, methodology, software, O.A.-A.; validation, C.V. and J.K.; formal analysis, O.A.-A. and J.K.; investigation, C.V. and J.K.; resources, O.A.-A., A.K. and J.K.; data curation, A.K. and J.K.; writing—original draft preparation, O.A.-A.; writing—review and editing, A.K., C.V. and J.K.; visualization, O.A.-A.; supervision, J.K.; project administration, C.V. and J.K. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Our study involves information freely available in a public domain (NWS COVID-19 Dashboard), which is open-source and accessible by anyone: https://gzt.whotur.com/links_list.php?page=list (accessed on 16 January 2021). Data were obtained from the dashboard, where they are appropriately anonymized, and informed consent was obtained at the time of original data collection.

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Data Availability Statement: Pictures, data, Excel sheets, SPSS documents, and related equations and figures are uploaded to the Mendeley data repository and available at the link: <https://data.mendeley.com/datasets/gpw4yt3bv2/4> (last version was accessed on 1 March 2022). The personal information of the cases was removed from all the documents.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Table of the basic reproduction number values in different cities and countries.

No	R0	Place	Reference
1	2.2	Wuhan, China	[56]
2	2.6	China	[57]
3	4.6	Hubei, China	[58]
4	4.7	Wuhan	[59]
	1.52	China	
	5.93	Hubei	
5	2.79	China	[60]
6	5.2	Wuhan, China	[61]
7	7.9	Wuhan, China	[62]
8	5.06	Heilongjiang, China	[63]
9	3.2	Wuhan, China	[64]
10	2.7	Wuhan, China	[65]
11	2.55	China	[66]
	1.78	S. Korea	
	3.47	Qom, Iran	
	1.82	Iran	
	3.37	Italy	
12	2.1, 3.2	Wuhan, China	[67]
		China	
13	2.24, 3.58	China	[68]
14	3.11	Wuhan, China	[69]
15	2.68	Wuhan, China	[70]
16	3.15	China	[71]
17	2.2	Wuhan, China	[72]
18	2.97	Anhui, China	[73]
19	2.6	S. Korea	[74]
	3.2	S. Korea	
	3.3	Italy	
	2.3	Italy	
20	1.59	S. Korea	[75]
21	2.6	Japan	[76]
22	2.79	Syria	[53]
	2.72	France	
	1.72	China	
	1.00	Nigeria	
	1.61	The United States	
	1.29	Russia	
	1.4	Yemen	
	1.25	India	

Table A1. Cont.

No	R0	Place	Reference
23	3.99	Syria	[54]
	3.5	Iraq	
	4.13	Iran	
	4.08	Israel	
	4.05	Cyprus	
	7.41	Turkey	
	2.7	Kuwait	
	3.39	Bahrain	
	4.18	Qatar	
	4.45	Saudi Arabia	
	2.73	The United Emirates	
	2.6	Oman	
	3.52	Jordan	
	3.35	Egypt	
3.16	Lebanon		
2.89	Palestine		
24	2.37	Africa	[77]
25	1.56	Cameroon	[78]
26	1.06	Iraq	[79]
	1.03	Egypt	
27	4.86	Iran	[80]
28	2.7	Shahroud, Iran	[81]
29	2.38	Italy	[82]
30	4.9	Italy	[83]
	3.8	Belgium	
	4.4	France	
	4.7	Germany	
	3.7	Netherlands	
	6.1	Spain	
	3.6	Switzerland	
	3.9	The United Kingdom	
5.8	The United States		
31	2.28	Pakistan	[84]
32	2.28	Malaysia	[85]
33	5.25	Brazil	[86]
34	2.3	Ontario, Canada	[87]
37	1.66	Sri Lanka	[88]

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