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ORIGINAL RESEARCH

Predicting the Number of Consultations by Emergency Medical Teams During Disasters Using a Constant Attenuation Model: Analyzing the Data of 6 Disasters in Japan and Mozambique Between 2016-2020

**Takahito Yoshida[1], Tomohito Hayashi[1], Odgerel Chimed-Ochir[1], Yui Yumiya[1], Ami Fukunaga[1], Akihiro Taji[1], Takashi Nakano[2,3], Yoichi Ikeda[2], Kenji Sasaki[2], Matchecane Cossa[4], Isse Ussene[4], Ryoma Kayano[5], Flavio Salio[6], Kouki Akahoshi[7], Yoshiki Toyokuni[7], Kayako Chishima[7], Seiji Mimura[7], Akinori Wakai[8], Hisayoshi Kondo[7], Yuichi Koido[7], Tatsuhiko Kubo[1]*

1. Department of Public Health and Health Policy, Graduate School of Biomedical and Health Sciences, Hiroshima University, 1-2-3 Kasumi, Minami-ku, Hiroshima City, Hiroshima 734-0037, Japan

2. Center for Infectious Disease Education and Research, Osaka University, 2-1 Yamadaoka Suita city, Osaka 565-0871, Japan

3. Research Center for Nuclear Physics, Osaka University, 10-1 Mihogaoka Ibaraki city, Osaka 567-0047, Japan

4. National Program of Surgery, Ministry of Health of Mozambique, Maputo, Mozambique; Avenida Eduardo Mondlane Maputo 1008, Mozambique

5. World Health Organization Centre for Health Development (WHO Kobe Centre), I.H.D. Centre Bldg. 9F, 1-5-1, Wakinohama-Kaigandori, Chuo-ku, Kobe-shi, Hyogo, 651-0073, Japan

6. Emergency Medical Teams, World Health Organization, Geneva, Switzerland, Avenue Appia 20, 1211 Geneva, Switzerland

7. National Hospital Organization Headquarters DMAT Secretariat MHLW Japan, 3256 Midori-cho Tachikawa, Tokyo 190-8579, Japan

8. National Hospital Organization Headquarters DMAT Secretariat MHLW Japan, Houenzaka 2-1-14 Chuo-ku Osaka City, Osaka 540-0006, Japan

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Abstract: **Introduction:** Predicting the number of emergency medical team (EMT) consultations that are needed following a natural or man-made disaster can help improve decisions regarding the dispatch and withdrawal of these teams. This study aimed to predict the number of consultations by EMTs using the K value and constant attenuation model.
Methods: Data were collected using the Japan-Surveillance in Post-Extreme Emergencies and Disasters (J-SPEED) and Minimum Data Set (MDS) for five disasters in Japan and one disaster in Mozambique. We compared the number of consultations, which was predicted based on K value and constant attenuation model with actual data collected with J-SPEED/Minimum Data Set (MDS) tools. **Results:** The total number of EMT consultations per disaster ranged from 684 to 18,468. The predicted curve and actual K data were similar for each of the disasters (R^2 from 0.953 to 0.997), but offset adjustments were needed for the Kumamoto earthquake and the Mozambique cyclone because their R^2 values were below 0.985. For the six disasters, the difference between the number of consultations predicted based on K values and the measured cumulative number of consultations ranged from ±1.0% to ±4.1%. **Conclusion:** The K value and constant attenuation model, although originally developed to predict the number of patients with COVID-19, provided reliable predictions of the number of EMT consultations required during six different disasters. This simple model may be useful for the coordination of future responses of EMTs during disasters.

Keywords: Prediction Algorithms; Models, Statistical; Emergency Medical Services; Dataset; Disasters

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*Corresponding Author: Tatsuhiko Kubo; Department of Public Health and Health Policy, Graduate School of Biomedical and Health Sciences, Hiroshima University, 1-2-3 Kasumi, Minami-ku, Hiroshima City, Hiroshima 734-0037, Japan. Tel: +81-82-257-5167, E-mail: tkubo@hiroshima-u.ac.jp, ORCID: https://orcid.org/0000-0001-8822-9181.

1. Introduction

Disasters triggered by natural hazards with sudden onset, such as floods, storms, and earthquakes, are becoming more common worldwide. In particular, the incidence of such disasters in 2022 surpassed the annual average of the past two decades (1), and there have been over 10,000 recorded disasters worldwide since 1970 (2). These disasters have signifi-

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cant impacts on the society and health, and require rapid responses from diverse professionals.
A disaster typically leads to the dispatch of Emergency Medical Teams (EMTs) who provide the medical care needed because of the sudden onset of injured and sick people. The World Health Organization (WHO) has proposed that EMTs operate under the coordination of the EMT Coordination Cell (EMTCC) (3), which faces various challenges during disaster response. For instance, existing resources are overwhelmed by disasters, and it is therefore crucial to optimize the number of EMTs and deploy the right mix of EMT personnel to avoid duplication of efforts and gaps in coverage (3, 4). However, it can be challenging to accurately determine the number and types of EMTs required during the acute phase of a disaster (5) and to determine the optimal timing for their withdrawal. The timely withdrawal of EMTs is crucial for preserving essential medical activities and ensuring that the objectives of EMTs were achieved. Factors such as patient load, the need for follow-up, and available alternative resources are considered in these decision-making processes. Predicting patient load is important for determining the timing of EMT withdrawal, and is also critical for identifying the need for medical resources and ensuring timely delivery of medical care to decrease deaths and injuries (6). Numerous studies have emphasized the importance of predicting consultation volumes for resource allocation, coordination of care, triage, and situational awareness (7–9).
The Great East Japan Earthquake in 2011 underscored the necessity for standardized EMT daily reporting procedures, and led to establishment of the Joint Committee for Disaster Medical Recording and a proposal for Japan Surveillance in Post-Extreme Emergencies and Disasters (J-SPEED). J-SPEED was inspired by the Surveillance in Post-Extreme Emergencies and Disasters (SPEED) system developed in the Republic of the Philippines, and was first activated during the 2016 Kumamoto Earthquake (10). It currently serves as a comprehensive framework for EMTs in Japan to compile real-time health data during disasters.
This study aimed to predict the number of consultations by an EMT following a disaster using the K value and constant attenuation model on J-SPEED and Minimum Data Set (MDS) records.

2. Methods

2.1. Study design and setting

This study aimed to evaluate the accuracy of K value and constant attenuation model, which was developed by Nakano et al. to predict the cumulative number of COVID-19 patients (11), in predicting the number of patient consultations with EMTs during disasters. We compared the number of consultations, which was predicted by K value and constant attenuation model with actual data collected with J-SPEED/Minimum Data Set (MDS) tools during five disasters in Japan and one disaster in Mozambique.
The Hiroshima University Ethics Committee examined and approved the ethics of all procedures used in this study (approval number: E–2059).

2.2. Participants

Data on the number of consultations from eight disasters were collected from J-SPEED or MDS from the years 2016 to 2020. Seven of these disasters occurred in Japan, and one was in Mozambique. Two Japanese disasters, namely the Northern Kyushu heavy rain in 2019 and Typhoon No. 15 in 2019, were excluded from analysis due to insufficient data coverage (periods less than 15 days). The impact of the 2018 West Japan heavy rain was significant, and required interventions by EMTs in three prefectures. However, the 38 consultations reported in Ehime Prefecture were limited to only 10 cases. Consequently, data from Ehime Prefecture were excluded from the analysis, but data focusing on consultations in Okayama and Hiroshima Prefectures were examined.

2.3. Data collection

The J-SPEED is a real-time data collection and reporting tool developed in 2015 to standardize daily reporting by Emergency Medical Teams (EMTs) during emergencies in Japan. The J-SPEED was based on the Surveillance in Post-Extreme Emergencies and Disasters (SPEED) of the Republic of the Philippines. J-SPEED enables EMTs in Japan to collect real-time health data during emergencies and disasters, covering 26 key items, including demographic information and health events.
The MDS is an international version of J-SPEED, which was endorsed by the World Health Organization in 2017. The MDS expands upon the J-SPEED framework by incorporating additional items, such as procedures performed, outcomes, and the relation of health events to the disaster. The MDS was first activated during Cyclone Idai in Mozambique in 2019.
In Japan, the number of consultations by EMTs is reported using the J-SPEED form, while the WHO MDS tool was used during Cyclone Idai. Both systems generate standardized daily reporting forms to facilitate coordination during disaster response and provide raw data in CSV (comma-separated value) format for detailed analysis. Further details about J-SPEED (12, 13) and MDS (14, 15), including their implementation and impact, can be found in the relevant reports and publications.

2.4. Statistical analysis

We estimated the K value as the primary statistical analysis in this study. The K value is an indicator of the cumulative number of patients during the most recent week, and the constant attenuation feature allows this indicator to predict future cumulative numbers of patients. The cumulative number of patients predicted by the constant attenuation model is consistent with the Gompertz model (16), which has been widely used in demography, cell biology, and other disciplines (17). These calculations rely solely on time series data of the target

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numerical variable, making it applicable even in the chaotic situations of disasters. As such, this model provides a user-friendly tool for prediction, because it only requires knowledge of the cumulative number of patients.
The K value and constant attenuation model was employed to predict the cumulative number of EMT consultations and is derived from the daily count of consultations recorded by J-SPEED/MDS during the onset of a disaster. The K value is defined by the following equation:

$$K(d) = 1 - \frac{N(d-7)}{N(d)}$$

where $N(d)$ and $N(d-7)$ are the cumulative number of consultations up to day d and day $d-7$ from the first day that J-SPEED data were collected. Given that $N(d)$ has a monotonic increase, the K value ranges from 0 to 1. Without loss of generality, the daily change in $N(d)$ can be expressed using the time-dependent exponential factor $a(d)$ as:

$$N(d+1) = e^{a(d)} N(d)$$

The proposed constant attenuation feature of this model assumes that $a(d)$ can be expressed as:

$$a(d+1) = ka(d)$$

The K value can then be approximated by a first-order linear function within a range ($0.25 < K < 0.9$), and when the slope of the function is K', k can be defined as:

$$k = 1 + 2.88K'$$

Under this assumption, when predicting the transition of the K value at a certain time, the measured K value can be approximated linearly and drawn as a straight line within the specified range ($0.25 < K < 0.9$). For lower values of K, the predicted K value can be drawn recursively using the formula:

$$K(d+1) = 1 - (1 - K(d))^k$$

The coefficient of determination, R^2, can then be calculated to determine the agreement between the predicted K values and the actual K values.
A large discrepancy between the predicted and actual K values on day d indicates a significant change in circumstances during that time period. In such instances, an offsetting process is used, in which the cumulative number of consultations $N(d)$ is reset to 0, and the K values are recalculated using the new cumulative number of consultations, with day d serving as the starting point:

$$K(d+1) = 1 - (1 - K(d))^k$$

The above equation also allows predictions of the transition of $N(d)$.
Then, $N_m(d)$ can be calculated as the seven-day moving average of the cumulative number of consultations:

$$N_m(d) = \frac{N(d-3) + N(d-2) + \cdots + N(d+2) + N(d+3)}{7}$$

If the last day with a measured K value greater than 0.25 is defined as day z, then $N_m(z-4)$, can be substituted for $N_m(z-3)$:

$$N_m(z-3) = e^{a(z-4)} N_m(z-4) a(z-4) = \log\left(\frac{N_m(z-3)}{N_m(z-4)}\right)$$

$$a(0) = \frac{1}{k^(z-4)} \times \log\left(\frac{N_m(z-3)}{N_m(z-4)}\right)$$

$$N(d) = N_m(z-4) \times e^{\frac{a(0)\left(k^{(z-4)} - k^d\right)}{1-k}}$$

Microsoft Excel (Microsoft Corp., Redmond, Washington, USA) was used for all calculations.

3. Results

3.1. Baseline characteristics of studied disasters

The final analysis included 13,925 consultations for five disasters reported in J-SPEED (Kumamoto earthquake, West Japan heavy rain, Hokkaido earthquake, Typhoon No. 19, and Kumamoto heavy rain) between 2016 and 2020 and 18,468 consultations for a 2019 cyclone in Mozambique reported in MDS.
The total number of EMT consultations per disaster ranged from 684 to 18,468. Table 1 shows the onset date, period of data collection by J-SPEED and MDS, and number of EMT consultations for each of the six disasters. Among the five disasters in Japan (two earthquakes, two torrential rains, and one typhoon), the EMTs were active for periods ranging from 27 to 48 days. In contrast, for the Mozambique cyclone, the EMTs were active for 108 days. EMTs began reporting within 10 days of onset of the West Japan heavy rain, within 12 days of onset of the Mozambique cyclone, and within 3 days of onset for the other disasters.
Figure 1 shows the daily number of consultations for each disaster (left) and the percentage of daily consultations relative to the total for each disaster (right). The Mozambique cyclone had the greatest number of consultations per day (755 consultations on day 10) followed by the West Japan heavy rain (616 consultations on day 9). However, relative to the total for each disaster, the Hokkaido earthquake on day 3 and the West Japan heavy rain on day 9 had the greatest percentages of daily consultations. In contrast, the Mozambique cyclone had relatively low percentages of daily consultations throughout the data collection period, and this percentage remained relatively steady, even after the peak on day 10. This variability in daily consultations among these six disasters underscores the absence of a uniform discernible pattern, even though each disaster had a large peak immediately following its onset.

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Table 1: Factors affecting the length of stay (LOS) in intensive care unit (ICU) patients undergoing CABG and their mean score out of 5

Name of Disaster	Date of Onset	Data Collection Period	Duration (day)	Number of EMT Consultations*
Kumamoto Earthquake**	14 April 2016	16 April 2016-2 June 2016	48	8,102
West Japan Heavy Rain	28 June 2018	8 July 2018-24 August 2018	48	3,582
Hokkaido Earthquake	6 September 2018	6 September 2018-7 October 2018	32	741
Mozambique Cyclone	15 March 2019	27 March 2019-12 July 2019	108	18,468
Typhoon N19	10 October 2019	13 October 2019-21 November 2019	40	684
Kumamoto Heavy Rain	3 July 2020	5 July 2020-31 July 2020	27	816

*The total number of consultations includes cases that resulted in deaths. **From April 16 to April 24, data is preliminary and only includes reports from limited areas. EMT: Emergency Medical Team.

3.2. Model agreement

Figure 2 shows the model calculations (for $0.25 < K < 0.9$) and actual data for the six disasters. In most cases, it took two days for the K value to drop below 0.9, at which time it was used for predictions ($d = 9$ days from the start of EMT reporting). However, it took 5 days for the K value to drop below 0.9 for the West Japan heavy rain and the Mozambique cyclone ($d = 12$ days from the start of EMT reporting).

The coefficient of determination, R^2, was close to 1.0 for each disaster, indicating high levels of agreement between the actual K data and the predictions. R^2 was somewhat lower (below 0.985) for the Kumamoto earthquake and the Mozambique cyclone, necessitating further analyses of these two disasters. Thus, the measured K values had a change in rate of decrease after the K values became calculable starting on the third day ($d = 10$) for the Kumamoto earthquake and starting on the nineteenth day ($d = 26$) for the Mozambique cyclone. We therefore offset the cumulative number of consultations to yield new K values for each disaster (Figure 3). In each case, the new coefficient of determination, R^2, was closer to 1.0, indicating a better fit of the prediction line.

Figure 4 shows the outcomes of predicting the change in the cumulative number of EMT consultations, $N(d)$, from the prediction lines obtained for the different K values for each disaster.

Table 2 presents the measured number of consultations recorded up to the end of each EMT reporting period and the projected cumulative number of consultations up to the same time based on the K value projection for each disaster. For each disaster, the difference between the measured and predicted numbers of EMT consultations was less than 5%. The parameter z (number of days required for prediction) ranged from 14 days (Hokkaido earthquake) to 44 days (Mozambique cyclone) from the start of EMT reporting, and was longer for the two disasters that were subjected to offsetting.

4. Discussion

We examined use of the K value and constant attenuation model, which was originally designed to predict the cumulative number of COVID-19 patients, for predicting patient loads during different disasters. We utilized data on the number of consultations provided by EMTs that were collected from the daily report forms of J-SPEED and MDS for six disasters (earthquakes, cyclones, and heavy rains) that occurred in Japan and Mozambique between 2016 and 2020. For each disaster, the difference between the measured and predicted cumulative number of consultations was less than 5%.

Our review of the literature showed that most prediction methods used in emergency management that consider natural and man-made disasters have taken one of two primary directions. Some prediction methods focus on logistic and infrastructural issues (18), and include forecasting logistic challenges (19), emergency evacuation (20), relief resource distribution (21), building and economic damages (22, 23), and hospital function during the days following a disaster (24). Other prediction methods center on methodologies for characterizing the emergency response of local hospitals to disasters by assessing patient treatment, triage processes, patient transfers (25), and estimates of the number of deaths from earthquakes (6). However, no suitable method has yet been proposed for predicting patient loads during disasters that require EMTs.

Most existing models (except the one proposed by Fujimoto et al. (6)) require multiple inputs to make predictions. However, recent advancements in disaster research have highlighted the importance of simple, readily applicable prediction methods that can be effectively employed to support real-time disaster response efforts. In emergency situations, where time is of the essence, prediction models must not only be accurate but also practical and quickly executable to ensure timely and effective decision-making (26). Recognizing this necessity, some researchers have contributed to this concept. For example, Fujimoto et al. introduced simple methods that can rapidly forecast the number of deaths and quantify the need for medical resources, including the deployment of medical experts. However, this previous model only predicts the number of deaths during earthquakes in Japan, not the number of patients requiring medical treatment. Since the number of medical treatments directly impacts EMT operations, there is therefore a more urgent need for these predictions than for predictions of deaths or economic losses. The model described herein, despite its simplicity, provided accurate predictions of patient loads in six different disasters.

The current model only requires the cumulative number of patient consultations during the initial days of a disaster

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Table 2: Accuracy in predicting the cumulative number of patients in six disasters

Name of Disaster	Total N of Consultations	Estimated of Consultations		Days of Data Collection	Day z*	
Kumamoto Earthquake	8,102	7,842.6	96.8%	48	26	**
West Japan Heavy Rain	3,582	3,435.1	95.9%	48	18	
Hokkaido Earthquake	741	750.2	101.2%	32	14	
Mozambique Cyclone	18,468	17,711.9	95.9%	108	44	**
Typhoon N19	684	675.6	98.8%	40	16	
Kumamoto Heavy Rain	816	824.4	101.0%	27	17	

* Day z is the last day with a measured K value greater than 0.25. **For offsetting disasters, day z is the last day the measured K value is greater than 0.25 after offsetting.

to predict future patient loads. Our findings demonstrated the usefulness of this approach for earthquakes, floods, tsunamis, and hurricanes in Japan and Mozambique. Because a disaster can occur almost anywhere and at almost any time, it can be challenging to rapidly estimate the cumulative number of medical cases as feedback to EMTs if extensive data collection is required for model inputs. Therefore, the ability to predict changes in the number of EMT consultations using a single parameter (the essence of the model described herein) makes our approach especially useful.

In the mathematical model used here, if there is a large discrepancy between the predicted and measured K values, then the cumulative number of consultations is reset to 0 and the K values are recalculated from this new starting point. We applied this offset for two of the disasters we analyzed. For the 2016 Kumamoto earthquake, we applied an offset on the tenth day after the start of J-SPEED data collection. This offset was needed because the lack of data collection outside the Aso district between April 16 and April 24 led to a sudden increase in consultations after April 25, and this manifested as an increased K value. Similarly, for the Mozambique cyclone, we applied an offset on the 19th day after obtaining the K values (corresponding to the 26th day after the start of data collection). This offset may have been needed because of further damage from another disaster (Cyclone Kenneth), which occurred in northern Mozambique on April 25 and affected more than 400,000 people. It is likely that the additional damage caused by this second cyclone influenced the K values. These changes in K values suggest the model can promptly detect changes, including alterations in aggregation methods and environmental factors. This feature could also assist in the early detection and mitigation of infectious disease outbreaks in emergency shelters. In general, an abrupt increase in the K value indicates a deviation from the expected trend and the need for proactive measures to address the different conditions.

Despite our implementation of these adjustments, the Mozambique cyclone dataset still had the lowest R^2 among the six disasters. This may be attributable to differences in EMT activities between Japan and Mozambique. More specifically, in Japan, patients can consult their local family doctors after the acute phase of a disaster. In contrast, in Mozambique, where the medical system is less robust, patients might seek long-term medical consultation from EMTs for conditions unrelated to the disaster (14). Additionally, the limited reporting from only one EMT during the May 14 to July 12 period in Mozambique may have led to bias.

The mathematical model employed in this study (originally designed for predicting COVID-19 infections) lacks an evidence-based explanation for its applicability to the field of disaster medicine. However, we speculate that mathematical similarities between the transmission of an infectious disease and the deployment of EMTs to disaster-affected areas explain the effectiveness of this model for the field of disaster medicine. When deciding to withdraw an EMT, each team must consider its own situation as well as the situations of other teams. For example, when one team starts to withdraw it is likely the nearby teams will also withdraw.

The K value approach used here can potentially be extended beyond disaster settings, and be used as a tool for post-disaster evaluations. Comparing the actual number of patients with the number predicted using the K value approach can provide a more comprehensive assessment of the measures taken and events that occurred. This evaluation can also provide a valuable foundation for the management of future disasters. For instance, analyzing the discrepancy between predicted and measured patient numbers can provide information regarding the effectiveness of different interventions, such as the deployment of EMTs, the timing of EMT withdrawal, and the causes of post-disaster outbreaks. The examination of past disasters, including the number of EMTs dispatched, the advantages and disadvantages of different timings for EMT withdrawal, and investigation of the causes of a disaster, may help to improve future strategies for disaster response. Moreover, when predictions are based on the same model, they can be compared at different scales and for different types of disasters. This comparative analysis can provide valuable insights into the generalizability and adaptability of the K value approach when used for different types of disasters, thereby enhancing its utility as a predictive tool for disaster management. Overall, leveraging the K value approach for post-disaster evaluation can be considered a systematic framework for learning from past experiences and improving responses to future disasters.

To improve the accuracy and timeliness of predictions for medical treatments during disasters, it may be necessary to adapt variables of the existing model so they align with the activity cycle of EMTs. Moreover, investing in advanced train-

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ing and ensuring consistent reporting practices among EMT members may further optimize the effectiveness of the K value approach for disaster responses.

When employing this forecasting method to determine the timing of EMT withdrawal, it is imperative to establish clear withdrawal criteria, such as the K value at the time of withdrawal. These withdrawal criteria should consider many factors, including the scale of the disaster, the number of EMTs deployed, the readiness of the affected area to receive patients, and political considerations. The establishment of specific withdrawal criteria remains a topic for future research.

5. Limitations

The K value approach has strengths and limitations when applied in disaster settings. A major advantage is that it can predict changes in the number of medical consultations using a single parameter, an important feature when encountering a chaotic and multifaceted disaster. This simplicity streamlines the prediction process and enables rapid decision-making. Additionally, our model employs a real-time adjustment mechanism that adapts to incoming data and unexpected surges, supporting Klus et al.'s assertion that dynamic adaptive systems flexibly adjust event types and sizes in real time based on changing data inputs (27).

One limitation of our approach is that inconsistency among EMT members regarding use of data collection tools such as J-SPEED may introduce errors in data collection and entry that could lead to discrepancies between predicted and measured numbers. A second limitation is that we directly applied a mathematical model that was originally developed for predicting COVID-19 cases, not the utilization of EMTs during disasters. However, the K value model was initially derived from the cumulative number of COVID-19 cases during the previous week to leverage the one-week cyclical pattern of COVID-19 testing. Although this approach leads to more stable predictions, it also means that the first K values are not accessible until 1 week later. When applied to disasters, this delay means it is difficult to estimate values soon after disaster onset. Disasters typically require urgent responses and require accurate predictions of the need for EMTs.

6. Conclusions

The K value and constant attenuation model, originally proposed for the COVID-19 epidemic, reliably predicted the number of EMT consultations during six different disasters. This straightforward method of prediction can potentially improve the activities of the Emergency Medical Team Coordination Cell, thereby significantly enhancing disaster medical operations.

7. Declarations

7.1. Acknowledgments

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7.2. Author Contribution

TY, TH, OC, YY, AF and TK conceived and designed the study. TY, TH and OC conducted data analysis. TY and TH drafted the manuscript. OC and TK edited the manuscript. AT, TN, YI, KS, MC, IU, RK, FS, KA, YT, KC, MS, AW, HK and YK reviewed the manuscript. TY and TK received research grants. All authors read and approved the final version of manuscript.

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7.4. Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7.5. Data Availability

The data utilized in this study was obtained from the J-SPEED Research Group for research purposes and will be available with the research group's permission.

7.6. Using artificial intelligence chatbots

The content of this article was not generated using any artificial intelligence chatbot.

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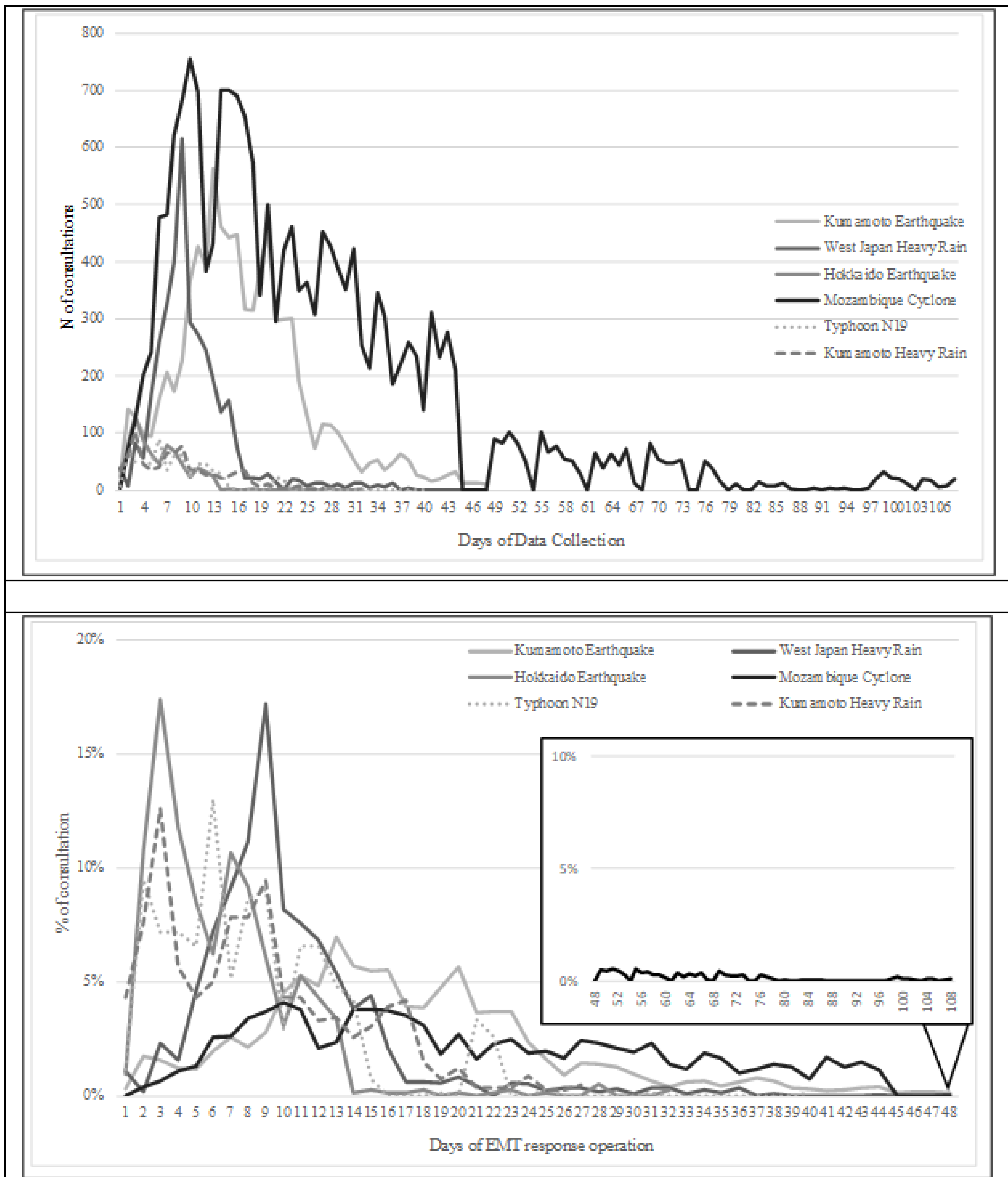

Figure 1: Total daily number and percentage of consultations for studied disasters. EMT: Emergency Medical Team.

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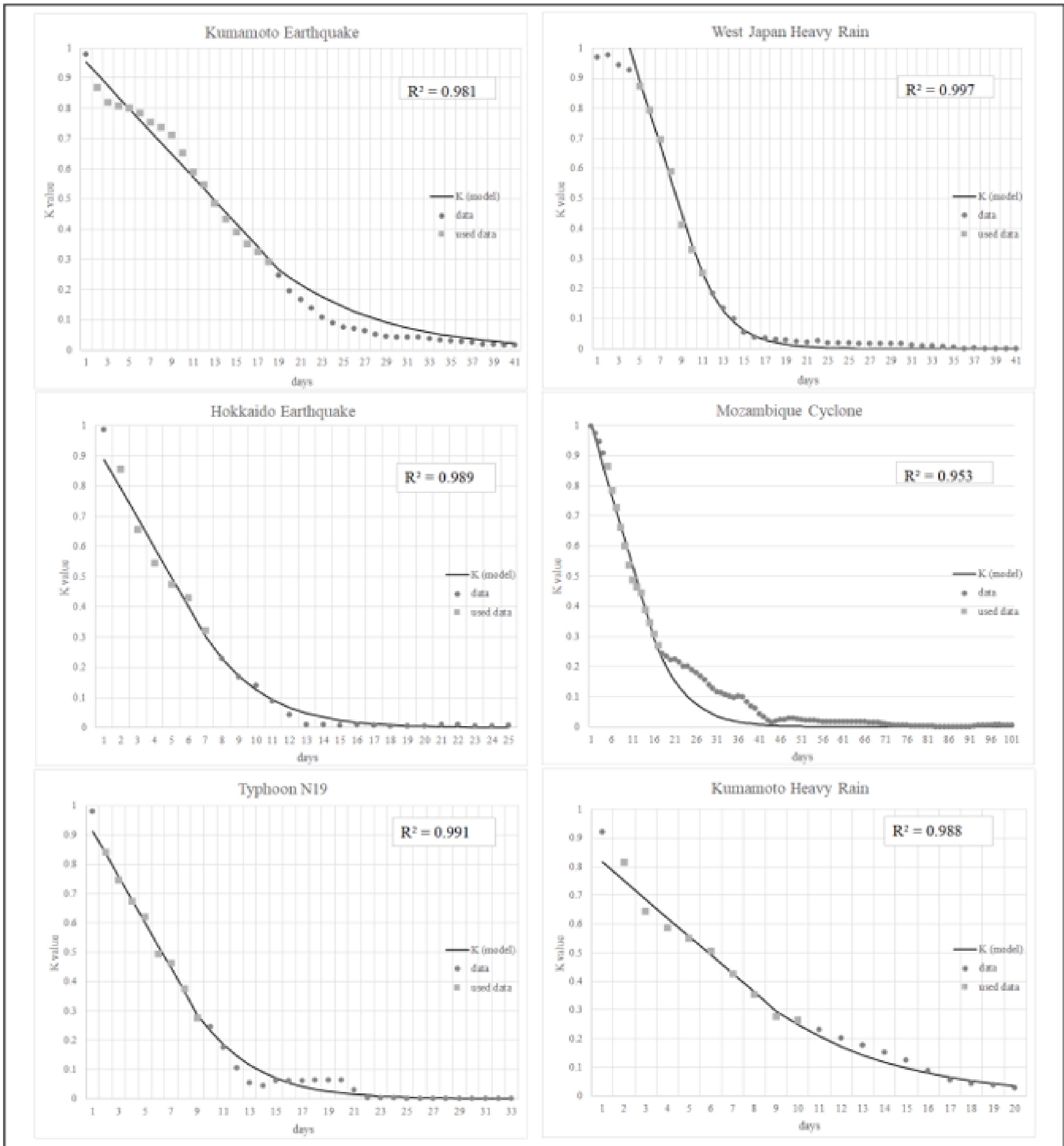

Figure 2: The agreement between studied model and actual data regarding the number of consultations following 6 disasters.

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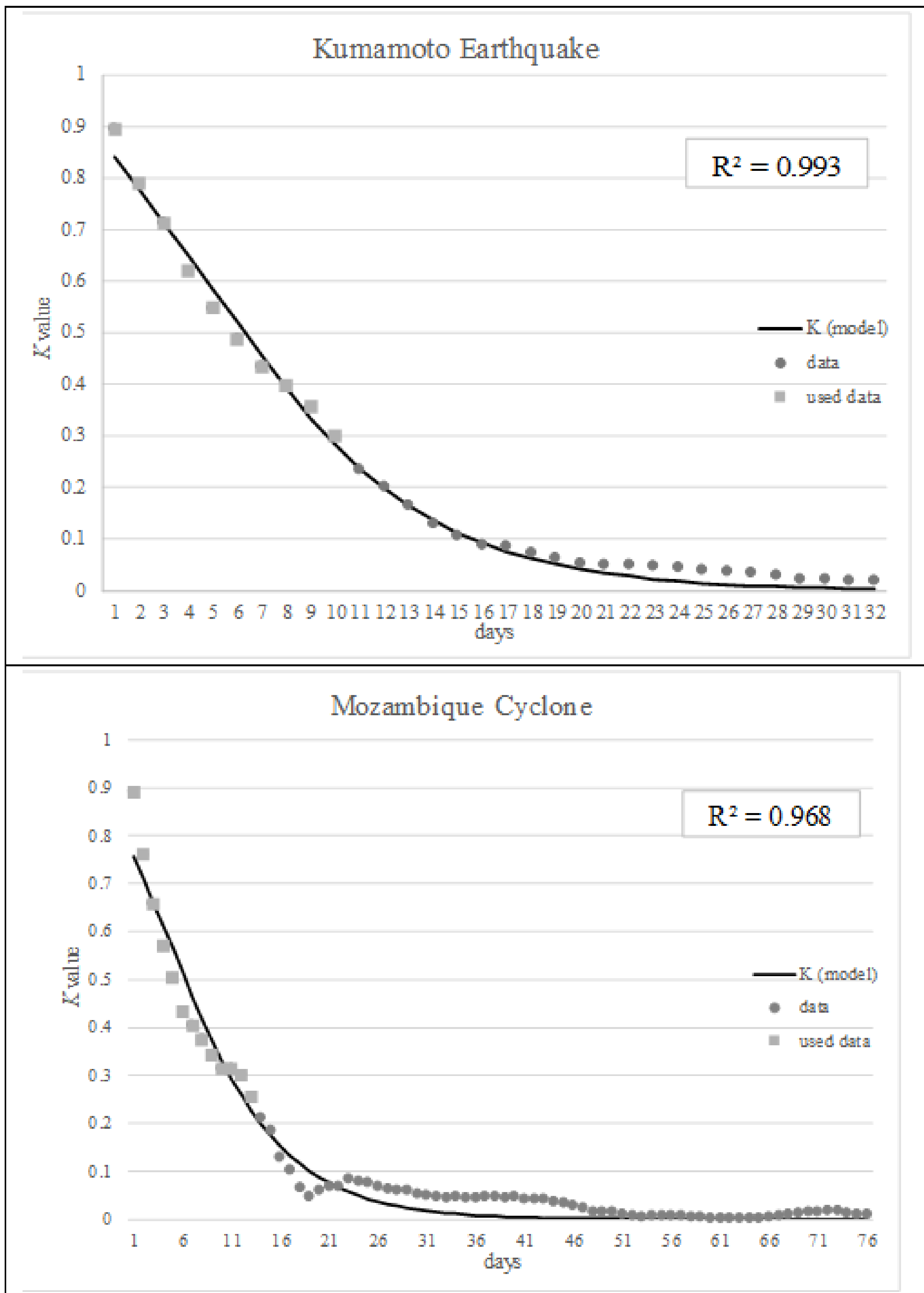

Figure 3: Model calculation after offsetting the cumulative number of consultations to yield new *K* values for two disasters.

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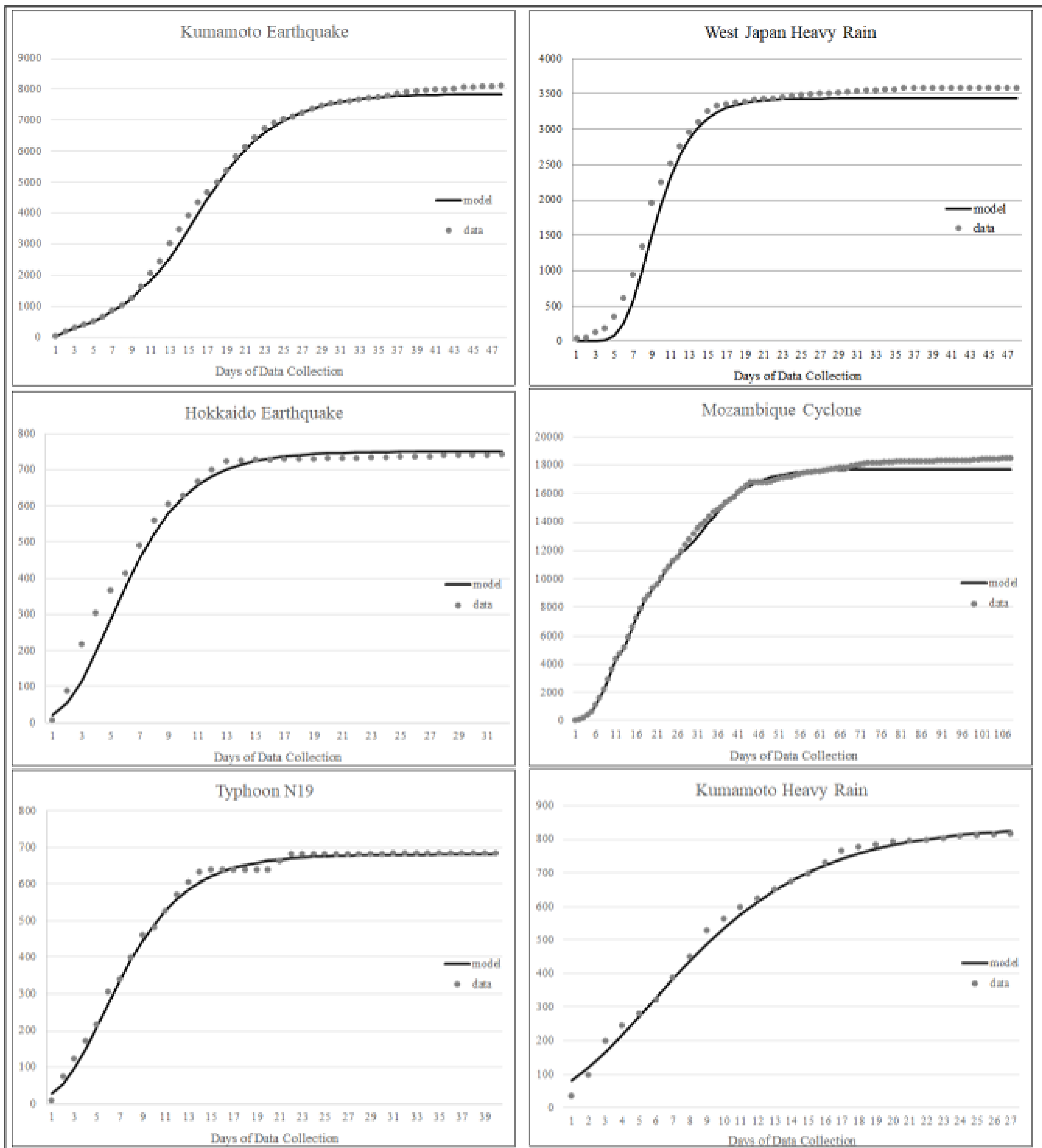

Figure 4: Outcomes of predicting the change in the cumulative number of consultations following studied disasters.

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