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Epidemic Peaks Forecasting on Re-emerging Diseases in Elderly People using the Grey Disaster Model

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Abstract

Climate change causes the spread of non-vector diseases due to the influence of climate uncertainty. The elderly group, which is vulnerable, is affected by such disasters. Therefore, the objectives of this study were to forecast epidemic peaks of food poisoning, which was found as one of the re-emerging diseases in elderly people in Khon Kaen Province, Maha Sarakham Province, and Roi Et Province, which are in the Northeastern region of Thailand by using 2 types of Grey Model: GM(1,1) and Discrete Grey Model (DGM). The monthly rate of food poisoning incidence per 100,000 elderly people from January 2017 to December 2020 i.e., 48 months in total were used in the study. The study result revealed that the DGM had higher forecasting effectiveness than that of the GM(1,1) in all three provinces. The food poisoning incidences in elderly people were forecasted to re-emerge from August to September 2021 in Khon Kaen Province, from August to September 2022 in Maha Sarakham Province, and from May to June 2022 in Roi Et Province. The results of this study are useful and helpful for the government, the Ministry of Public Health and related cooperatives to effectively help services planning resource preparation and prevention measures.

Keywords:

Epidemic Peaks; Grey Disaster Model; Re-emerging Diseases; GM(1,1).

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1- Introduction

Climate change causes seasonal infectious diseases due to the influence of climate uncertainty such as temperature and humidity as parts of climate variation. Moreover, the spread of non-vector diseases such as diarrhea and food poisoning is sometimes affected by climate change. The population structure of Thailand has changed into an aging society. In 2020, the northeastern region contained the largest number of elderly people. According to the Ministry of Social Development and Human Security, the number of elderly people at the age of 60 years upward in the next 20 years is estimated to increase up to 30%.

The forecasting of diseases and health threats is very important because the forecasting results allow surveillance on epidemiological diseases for the benefits of resource planning, and disease prevention and treatments in an effective way. Ju-Long (1982, 1989) [1-2] presents the Grey Model or GM(1,1) by basing the study principles on discrete data, uncertainty data distribution, and the limited number of data. The theory of GM(1,1) is widely used. In addition, Xie and Liu (2008) [3] develop the Discrete Grey Model (DGM) from the effective improvement of the GM(1,1). The models

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are widely used in medicines [4-9], and other areas such as petroleum, geological engineering, industry, management, marketing, and agriculture [10-23]. In medicines and public health, the spread of diseases is affected by several uncertain factors, so the Grey theory with dynamic changes is suitable to be used. The GM(1,1) is popularly used in forecasting diseases and death rates from epidemics. As a result, this research studied the epidemic peaks of food poisoning of elderly people in Khon Kaen Province, Maha Sarakham Province, and Roi Et Province (Thailand) since those provinces were almost in the top ranks of elderly people with food poisoning in the middle northeastern region. The analyses with GM(1,1) and DGM are useful for planning resources and preventing the diseases effectively.

2- Data Preparation and Methodology

2-1- Data

The data in this research were the monthly rate of food poisoning incidence per 100,000 elderly people from January 2017 – December 2020 i.e., 48 months in total in Khon Kaen Province, Maha Sarakham Province, and Roi Et Province.

2-2- GM(1,1)

GM(1,1) is the model of the Grey theory of prediction with one variable .The first order Grey model is created with a few data (four or more .(Its procedure is as follows:

- The existing data with the *n* sample units are represented in $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n))$, where $X^{(0)}$ is the series of data.
- Calculate the cumulative sum of the existing data $X^{(0)}$ in the form of a cumulative sum series.

$$X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)\right) = \left(\sum_{i=1}^{1} x^{(0)}(i), \sum_{i=1}^{2} x^{(0)}(i), ..., \sum_{i=1}^{n} x^{(0)}(i)\right).$$
(1)

• Calculate $Z^{(1)}$, the means from (1) as:

$$Z^{(1)} = \left(z^{(1)}(2), z^{(1)}(3), ..., z^{(1)}(n)\right),$$
(2)

where $z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1)$; k = 2, 3, ..., n.

• Calculate for the differential equation of GM(1,1) with $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$.

The resulting derivative of a function is
$$x^{(0)}(k) + az^{(1)}(k) = b$$
 where *a* and *b* are the parameters of GM(1,1).
That is, $\begin{bmatrix} a & b \end{bmatrix}^T = (B^T B)^{-1} B^T Y$, (3)

where
$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}$$
 and $B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}$.

• The forecasting equation can be calculated by;

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}$$
(4)

And the new equation is adjusted as follows:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1-e^a) \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-ak} .$$
(5)

It is called the time response equation.

2-3-Discrete Grey Model (DGM)

The DGM procedure is as follows:

• The equation
$$x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2$$
 (6)

It is called the Discrete Grey Model (DGM).

•
$$\hat{\beta} = (\beta_1 \ \beta_2)^T$$
 is the series of parameters where $Y = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}n \end{bmatrix}$ and $B = \begin{bmatrix} x^{(1)}(1) & 1 \\ x^{(1)}(2) & 1 \\ \vdots & \vdots \\ x^{(1)}(n-1) & 1 \end{bmatrix}$.

The least square method is used to estimate the parameters in the equation:

$$\hat{x}^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2,$$
(7)
where $\hat{\beta} = (B^T B)^{-1} B^T Y.$

• Let $x^{(1)}(1) = x^{(0)}(1)$, then the recursive function is used with the following setting:

$$\hat{x}^{(1)}(k+1) = \beta_1^k x^{(0)}(1) + \frac{1 - \beta_1^k}{1 - \beta_1} \times \beta_2,$$
(8)

or
$$\hat{x}^{(1)}(k+1) = \beta_1^k \left(x^{(0)}(1) - \frac{\beta_2}{1-\beta_1} \right) + \frac{\beta_2}{1-\beta_1},$$
 (9)

where k = 1, 2, ..., n-1.

Then restore the value of $\hat{x}^{(0)}(k)$, and the forecasting equation of DGM is obtained as follows:

$$\hat{x}^{(0)}(k+1) = \alpha^{(1)}\hat{x}^{(1)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), \qquad (10)$$

where k = 1, 2, ..., n-1.

2-4- Model Accuracy Test

The model accuracy tests are as follows;

• Mean Relative Error

$$\overline{\Delta} = \frac{1}{n-1} \sum_{k=2}^{n} \Delta_k = \frac{1}{n-1} \sum_{k=2}^{n} \left| \frac{\varepsilon(k)}{x^{(0)}(k)} \right|.$$
(11)

For the given α , when $\overline{\Delta} < \alpha$ and $\Delta_n < \alpha$ are true, the forecasting model is regarded as satisfied.

• Absolute Degree of Incidence;

$$\varepsilon = \frac{1 + |s_0| + |s_i|}{1 + |s_0| + |s_i| + |s_i - s_0|},\tag{12}$$

where
$$|s_0| = \left|\sum_{k=2}^{n-1} x_0^0(k) + \frac{1}{2} x_0^0(n)\right|$$
 and $|s_i| = \left|\sum_{k=2}^{n-1} x_i^0(k) + \frac{1}{2} x_i^0(n)\right|$

Let ε as the absolute value of the incidence level among raw data of $X^{(0)}$ and the simulated values for determining $\varepsilon_0 > 0$. If the absolute value of the incidence level is in accordance with $\varepsilon > \varepsilon_0$, the forecasting model is regarded as satisfied.

• Variance Ratio

$$C = \frac{S_1}{S_2} = \frac{\sqrt{\frac{1}{2} \sum_{k=1}^n (\varepsilon(k) - \overline{\varepsilon})^2}}{\sqrt{\frac{1}{2} \sum_{k=1}^n (x^{(0)}(k) - \overline{x})^2}}.$$
(13)

For determining $C_0 > 0$, if the variance ratio is $C = S_2 / S_1 < C_0$, the forecasting model is considered as satisfied.

• Small Error Probability

If $p = P(|(\varepsilon(k) - \overline{\varepsilon}| < 0.6745S_1))$ is calculated for probability of small errors and for determining $p_0 > 0$; where $p > p_0$, the forecasting model is regarded as satisfied.

The used scale for testing the model accuracy is illustrated in Table 1.

Accuracy scale	Mean relative error $(\overline{\Delta})$	Degree of incidence (\$\varepsilon)	Variance ratio (c)	Small error probability (p)
1 st level	≤0.01	≥0.90	≤0.35	≥0.95
2 nd level	0.01 - 0.05	0.80 - 0.90	0.35 - 0.50	0.80 - 0.95
3 rd level	0.05 - 0.10	0.70 - 0.80	0.50 - 0.65	0.70 - 0.80
4 th level	0.10 - 0.20	0.60 - 0.70	0.65 - 0.80	0.60 - 0.70

Table 1. Scales of accuracy for model testing.

Figure 1 shows the procedure for processing this research.

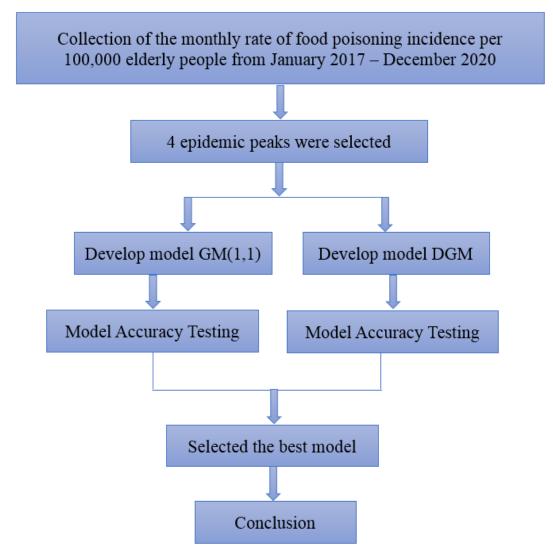


Figure 1. Flowchart of the research methodology.

3- Results and Discussion

Table 2 shows the monthly rate of food poisoning incidence per 100,000 elderly people from January 2017– December 2020 in Khon Kaen Province, Maha Sarakham Province, and Roi Et Province. The data at 4 epidemic peaks were selected for the analyses with GM(1,1) and DGM as shown in Figures 2 to 4.

month-year	Time series value	w ₁	<i>w</i> ₂	<i>w</i> ₃	month-year	Time series value	w_1	<i>w</i> ₂	<i>w</i> ₃
Jan-17	1	88.73	73.39	106.21	Jan-19	25	99.45	42.64	91.46
Feb-17	2	69.25	43.88	88.35	Feb-19	26	76.43	44.03	59.79
Mar-17	3	89.78	55.23	96.07	Mar-19	27	74.76	41.24	89.23
Apr-17	4	81.78	76.42	89.80	Apr-19	28	76.09	46.13	78.08
May-17	5	85.60	77.18	91.25	May-19	29	82.43	47.53	98.16
Jun-17	6	82.47	75.66	98.01	Jun-19	30	87.44	46.13	109.31
Jul-17	7	73.42	89.28	94.63	Jul-19	31	94.45	69.20	116.45
Aug-17	8	61.24	72.64	93.66	Aug-19	32	86.77	60.81	79.86
Sep-17	9	68.55	75.66	113.46	Sep-19	33	98.79	53.12	99.50
Oct-17	10	62.64	44.64	85.94	Oct-19	34	72.75	52.42	94.14
Nov-17	11	52.89	46.91	75.32	Nov-19	35	65.41	29.36	58.00
Dec-17	12	86.30	61.29	68.56	Dec-19	36	69.08	34.25	63.80
Jan-18	13	85.32	63.39	91.06	Jan-20	37	72.07	43.66	75.65
Feb-18	14	86.77	71.40	80.37	Feb-20	38	60.73	26.19	66.19
Mar-18	15	90.11	49.55	72.47	Mar-20	39	65.94	26.19	64.47
Apr-18	16	97.78	63.39	85.02	Apr-20	40	49.38	22.84	42.98
May-18	17	87.10	68.49	102.67	May-20	41	55.21	23.51	68.34
Jun-18	18	85.77	59.75	100.81	Jun-20	42	66.25	36.94	86.82
Jul-18	19	73.09	74.32	89.20	Jul-20	43	74.22	42.31	88.54
Aug-18	20	74.42	66.30	107.78	Aug-20	44	69.01	52.39	118.63
Sep-18	21	76.09	67.76	101.74	Sep-20	45	61.65	53.06	110.03
Oct-18	22	65.75	58.29	71.08	Oct-20	46	38.34	24.18	71.78
Nov-18	23	64.08	51.00	68.29	Nov-20	47	35.88	27.54	58.45
Dec-18	24	83.43	50.27	72.94	Dec-20	48	29.75	33.58	52.01

Table 2. The monthly rate of food poisoning incidence per 100,000 elderly people from January 2017 – December 2020.

Note: w_1 is the rate of food poisoning incidence per 100,000 elderly people in Khon Kaen Province. w_2 is the rate of food poisoning incidence per 100,000 elderly people in Maha Sarakham Province. w_{13} is the rate of food poisoning incidence per 100,000 elderly people in Roi Et Province.

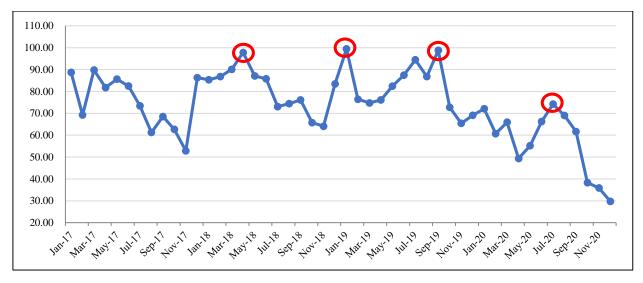


Figure 2. The rate of food poisoning incidence per 100,000 elderly people in Khon Kaen Province at 4 epidemic peaks selected for the model analyses.



Figure 3. The rate of food poisoning incidence per 100,000 elderly people in Maha Sarakham Province at 4 epidemic peaks selected for the model analyses.

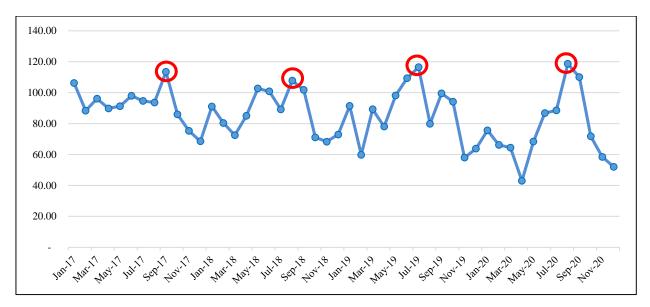


Figure 4. The rate of food poisoning incidence per 100,000 elderly people in Roi Et Province at 4 epidemic peaks selected for the model analyses.

Figures 2 to 4 illustrate the rate of food poisoning incidence per 100,000 elderly people at 4 selected epidemic peaks. The data used were in: April 2018, January 2019, September 2019, and July 2020 in Khon Kaen Province; in July 2017, July 2018, July 2019, and September 2020 in Maha Sarakham Province; and in September 2017, August 2018, July 2019, and August 2020 in Roi Et Province. These data were analyzed to obtain the forecasting models of GM(1,1) and DGM in each province are shown in Table 3. The values of forecasting and relative errors of GM(1,1) and DGM in each province are shown in Table 4, whereas the results from the model accuracy testing of GM)1,1 (and DGM in each province are shown in Table 5.

Province	$X^{(0)}$	GM(1,1)	DGM
Khon Kaen	$X^{(0)} = (16 \ 25 \ 33 \ 43)$	$\hat{x}^{(0)}(k+1) = 19.05288e^{0.26838k}$	$\hat{x}^{(0)}(k+1) = (25.09098) \left(1.30996^{k-1} \right)$
Maha Sarakham	$X^{(0)} = (7 \ 19 \ 31 \ 45)$	$\hat{x}^{(0)}(k+1) = 12.95167e^{0.40908k}$	$\hat{x}^{(0)}(k+1) = (19.85976) (1.51334^{k-1})$
Roi Et	$X^{(0)} = (9 \ 20 \ 31 \ 44)$	$\hat{x}^{(0)}(k+1) = 13.92074e^{0.37839k}$	$\hat{x}^{(0)}(k+1) = (19.85976) (1.46618^{k-1})$

Table 3. Forecasting model	of GM(1,1)	and DGM.
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Duranium	$X^{(0)}$	Original	GM(1,1)	DGM		
Province	$X^{(0)}$	(month)	Forecast (month)	Relative errors	Forecast (month)	Relative errors	
	$x^{(0)}(1)$	16	-	-	-	-	
121 12	$x^{(0)}(2)$	25	24.91817	0.00327	25.09098	0.00364	
Khon Kaen	$x^{(0)}(3)$	33	32.58905	0.01245	32.86830	0.00399	
	$x^{(0)}(4)$	43	42.62135	0.00881	43.05630	0.00131	
	$x^{(0)}(1)$	7	-	-	-	-	
Maha Sarakham	$x^{(0)}(2)$	19	19.49778	0.02620	19.85976	0.04525	
	$x^{(0)}(3)$	31	29.35246	0.05315	30.05464	0.03050	
	$x^{(0)}(4)$	45	44.18795	0.01805	45.48301	0.01073	
	$x^{(0)}(1)$	9	-	-	-	-	
Roi Et	$x^{(0)}(2)$	20	20.32337	0.01617	20.63377	0.03169	
K01 EI	$x^{(0)}(3)$	31	29.67080	0.04288	30.25280	0.02410	
	$x^{(0)}(4)$	44	43.31744	0.01551	44.35600	0.00809	

Table 4. The values of forecasting and relative errors of GM(1,1) and DGM.

Table 5. The model accuracy	testing of GM(1,1) and DGM.
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Province	Model	Mean relative error $(\overline{\Delta})$	Degree of incidence (&)	Variance ratio (c)	Small error probability (p)				
	GM(1,1)	00818.0 (1 st level)	84909.0 (2 nd level)	01804.0 (1 st level)	1 (1 st level)				
Khon Kaen	DGM	00298.0 (1 st level)	99985.0 (1 st level)	00851.0 (1 st level)	1 (1 st level)				
		The best model is DGM.							
			$\hat{x}^{(0)}(5) = 56.402$	23					
	GM(1,1)	00032.0 (1 st level)	96670.0 (1 st level)	05784.0 (1 st level)	1 1 st level)				
Maha Sarakham	DGM	00029.0 (1 st level)	99735.0 (1 st level)	04793.0 (1 st level)	1 (1 st level)				
	The best model is DGM.								
			$\hat{x}^{(0)}(5) = 68.8314$	43					
	GM(1,1)	00025.0 (1 st level)	99061.0 (1 st level)	04910.0 (1 st level)	1 (1 st level)				
Roi Et	DGM	00021.0 (1 st level)	99824.0 (1 st level)	03988.0 (1 st level)	1 (1 st level)				
	The best model is DGM.								
			$\hat{x}^{(0)}(5) = 65.033$	83					

In this study, the incidence rate of food poisoning of elderly people was conducted in Khon Kaen Province, Maha Sarakham Province and Roi Et Province which are located in the Northeastern region of Thailand. It was found that the 4 epidemic peaks of food poisoning incidence rate of elderly people in Maha Sarakham Province and Roi Et Province occurred from July to September, which is during the rainy season. In Khon Kaen Province, 4 epidemic peaks of food poisoning incidence rate of elderly people occurred in April 2018, January 2019, September 2019, and July 2020. It is shown that the first epidemic peak occurred during the summer season and tends to occur during the rainy season. The rainy season of Thailand is tropical and the pathogens may be growing as well. If people are not careful when eating, it may result in gastrointestinal diseases such as food poisoning, especially in the elderly people with low immunity, it can lead to death. In this research, the GM(1,1) model and the DGM model were used to construct the grey disaster model. The simulation results showed that the DGM model had a better performance. Then, the DGM model was chosen to make the prediction, which is corresponding to Shen et al. [5].

4- Conclusion

Grey disaster prediction, the GM(1,1) and DGM, is important to predict the time of abnormal values, and propose the forecast of the exact times of forthcoming disasters to prepare ahead of time for the worst situation. In this study, the GM(1,1) and DGM were used for forecasting the epidemic peaks of food poisoning incidence in the elderly people in Khon Kaen Province, Maha Sarakham Province, and Roi Et Province in Thailand .The study found that the DGM had higher forecasting effectiveness than that of the GM(1,1) in all three provinces .When the DGM is used in forecasting, the forecasting value in Khon Kaen Province was found at $\hat{x}^{(0)}(5) = 56.40223$, meaning that food poisoning incidence would re-emerge in elderly people from August to September 2021 and the mean relative error of the DGM model is 0.298% .In Maha Sarakham Province, the forecasting value was found at $\hat{x}^{(0)}(5) = 68.83143$, meaning that food poisoning incidence would re-emerge in elderly people from August to September 2022 and the mean relative error of the DGM model is 0.029%. In addition, the forecasting value in Roi Et Province was found at $\hat{x}^{(0)}(5) = 65.03383$, meaning that food poisoning incidence would re-emerge in elderly people from May to June 2022 and the mean relative error of the DGM model is 0.021%. Although the forecasting with Grey theory is highly effective and has yielded good results, it may not be appropriate for all situations. Moreover, the forecasting with Grey theory is more accurate in the short term but its accuracy in long-term forecasting may decrease [24]. Therefore, we should consider and analyze the actual situation and select a suitable model and adapt it to the situation of the disease. This makes it possible to take full advantage of forecasting models to maximize long-term benefits.

5- Declarations

5-1-Author Contributions

Conceptualization, N.C., P.G., B.K. and M.C.; methodology, M.C.; software, M.C.; validation, P.G. and B.K.; formal analysis, M.C.; investigation, B.K. and M.C.; resources, N.C. and P.G.; data curation, N.C., P.G. and P.B.; writing - original draft preparation, N.C.; writing - review and editing, B.K.; visualization, P.B.; corresponding author, M.C.; project administration, N.C.; funding acquisition, N.C. All authors have read and agreed to the published version of the manuscript.

5-2-Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5-3-Funding

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5-4-Acknowledgements

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5-5-Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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