Rainfall Prediction in Vietnam Using Grey Forecasting Model*

Nguyen-Nhu-Y Ho[1 0000−0002−7188−7927], Phuong Mai Nguyen[1,** 0000−0002−2704−9707], Phuong-Huyen Do[1], Huong-Trang Pham[1], and Nam D. Vo[2 0000−0001−5469−5707]

[1] International School, Vietnam National University, Hanoi, Vietnam
hngny@vnu.edu.vn; mainp@vnu.edu.vn; huyendp@isvnu.vn; trangph@vnu.edu.vn
[2] The University of Danang, Danang, Vietnam
vdnam@ac.udn.vn

Abstract. Vietnam is an agriculture-based country that is heavily affected by the climate change when El Niño is causing a significant impact on the rainfall of the country. In such a context, it becomes harder to predict the rainfall without applying modern methods and techniques. Thus, Vietnamese farmers have to deal with increasing difficulties in making choices of crops to grow, and irrigation plans for higher output and income if they still base on their old cultivation habit and subjective prediction of climate condition. Regarding the mentioned issue, this paper modifies an integrative framework that uses Grey (1;1) model to forecast the rainfall in Vietnam. Data of the rainfall amount from 2017 to 2020 in 15 meteorological regions throughout the country were collected to put into the Grey (1,1) forecasting model. The computation results show the total rainfall prediction for four consecutive years from 2021 to 2024 in 15 selected regions. These results will be useful for farmers in making their cultivation choices and other governing agencies to alter the agriculture related policies.

Keywords: Rainfall prediction · Grey model · Forecasting model.

1 Introduction

Rainfall is significant for agriculture as well as human beings and animals. Agriculture production is highly dependent upon precipitation, which falls in the form of rain [7]. Dependence on uncertain rainfall and exposure to unmitigated climate risks are major obstacles to efforts to intensify agricultural production

** Correspoding author: mainp@vnu.edu.vn

and enhance rural livelihoods sustainably, and causes negative impacts. According to Purdy et al., in areas with rainy and dry seasons, soil nutrients diminish and erosion increases during the rainy season [9]. The previous dry season leads to food shortages in the rainy season, as the crops have yet to mature. In addition, excessive rain during short periods of time often causes flash floods. Climate shocks such as drought and floods lead not only to the loss of life but also the long-term loss of livelihood through loss of productive assets, impaired health and destroyed infrastructure. It is insisted that the uncertainty associated with climate variability is a disincentive to investment and adoption of agricultural technologies and market opportunities, prompting the risk-averse farmer to favor precautionary strategies that buffer against climatic extremes over activities that are more profitable on average [6,5]. To the degree that climatic uncertainty adversely impacts farmer livelihoods, forecast information that reduces uncertainty becomes increasingly important. This type of information enables farmers to intensify production, replenish soil nutrients, motivates them to adopt improved technology to more effectively protect their families and farms against the long-term consequences of adverse extremes [1,4].

Vietnam is an agricultural-based country with a long history dating back to a thousand years ago. Agriculture is contributing about 20% to the national GDP. As an agricultural country, most of the poor live on agriculture and fishing. However, the cultivation practices in many rural areas are still straightforward without applying high technologies. Consequently, agriculture production depends heavily on the climate. Notably, Vietnam is assessed by the United Nations Development Organization as one of the top five countries in the world that is most directly vulnerable to climate change. The impacts of climate change such as sea-level rise, floods, droughts, salt-water intrusion, and extreme weather are becoming more and more apparent, causing damage to agriculture and Vietnam's economy in general.

For example, according to the analysis of the World Resources Institute on the impact of floods on GDP, Vietnam ranked fourth out of 164 surveyed countries in terms of the severe harm of floods to the whole economy. Floods are estimated to cause a loss of 2.3% of Vietnam's GDP every year. Moreover, salt-water intrusion reduces the area of arable farming land, from which the coefficient of land use may reduce from 3-4 times/year to 1-1.5 times/year. According to research results of the Institute of Agricultural Environment (Ministry of Agriculture and Rural Development), climate change reduces the yield of some key crops. Specifically, Spring rice yield will decrease by 0.41 tons/ha in 2030 and 0.72 tons in 2050. Maize yield is likely to fall by 0.44 tons/ha in 2030 and 0.78 tons in 2050. It is forecasted that by 2100, the Mekong Delta is at risk of being flooded with 89,473 hectares, which means that this area will lose about 7.6 million tons of rice/year if the sea level rises 100 cm. At that time, Vietnam is at risk of severe food shortages and poverty.

In addition, the increase of storms also decreases the GDP growth rate of Vietnam. If the average growth rate is 5.4% annually, the growth rate affected by hurricanes will be about 5.32% to 5.39%. The sea-level rise scenarios show that even the mildest impact level will cause GDP from 2046 to 2050 to decrease by 0 to 2.5%. Meanwhile, because Vietnam's GDP by 2050 is forecasted to be more than 500 billion USD, the value of the damage caused by climate change is about 40 billion USD. This damage is relatively significant but can be minimized with appropriate adaptation policies.

In this regard, it is essential to proactively assess and forecast the fluctuation of several critical elements in the agriculture sector, such as rainfall, to respond and develop a suitable and sustainable agriculture sector promptly. Hence, it is suggested using algorithms to predict seasonal rainfall a part of the solution for hydro-meteorological forecasting. Therefore, this paper proposes a modified framework using the Grey forecasting model to predict future precipitation trends of 15 meteorological regions in Vietnam from 2021 to 2024.

2 Methodology

2.1 Grey Forecasting Generation Theory

In the agriculture sector, forecasting is an essential determinant of operational performance. A dynamic Grey forecasting model is applied in this paper to improve forecasting accuracy. The Grey system theory, established by Deng in 1982, is a new method that focuses on the study of problems involving small samples and poor information [2]. Grey forecasting GM(1,n) is the most widely used model. Grey theory is a truly multidisciplinary and generic theory dealing with systems characterized by imperfect information or for which information is lacking. The fields covered by Grey theory include systems analysis, data processing, modeling, prediction, decision-making, and control. Grey forecasting models have been extensively used in many applications. The GM(1, 1) is one of the most frequently used Grey forecasting models. This model is a time series forecasting one, encompassing a group of differential equations adapted for parameter variance rather than a first-order differential equation. Its difference equations have structures that vary with time rather than being general difference equations. Consequently, Grey forecasting model is a good tool for predicting the values of the future mutual relationship among these factors based on a small amount of data [8].

GM(1,1) is the central model that has been most widely employed, and discrete Grey models are a class of new models we initially developed [8]. Let $X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right)$ be a sequence of raw data. Denote its accumulation-generated sequence by $X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right)$. Then

$$X^{(0)}(k) + ax^{(1)}(k) = b \tag{1}$$

is refered to as the original form of the GM(1,1) model, where the symbol GM(1,1) stands for "first-order Grey model in one variable".

Let $Z^{(1)} = \left(z^{(1)}(1), z^{(1)}(2), \cdots, z^{(1)}(n)\right)$ be the sequence generated from $X^{(1)}$ by the adjacent neighbor means. That is,

$$z^{(1)}(k) = \frac{1}{2}\Big(x^{(1)}(k) + x^{(1)}(k-1)\Big), \qquad k = 2, 3, \cdots, n \tag{2}$$

Then

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{3}$$

is refered to as the basic form of the GM(1,1) model.

Theorem 1. *Let $X^{(0)}$, $X^{(1)}$, and $Z^{(1)}$ be the same as above accept that $X^{(0)}$ is non-negative. If $\hat{a} = (a, b)^T$ is sequence of parameter, and*

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \tag{4}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & 1 \\ -z^{(1)}(n) & 1 \end{bmatrix}, \tag{5}$$

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} \tag{6}$$

the least squares estimate sequence of the GM(1,1) model Eq.(3) *satisfies $\hat{a} = (B^TB)^{-1}B^TY$.*

Continuing all the notations from Theorem 1, if $[a, b]^T = (B^TB)^{-1}B^TY$, then $\frac{d(x)^1}{dt} + ax^1 = b$ is a whitenization equation of the GM(1,1) model in the Eq.(3). Formula to solve the values a and b are as follow

$$a = \frac{\sum_{k=2}^{n} z^{(1)}(k) \times \sum_{k=2}^{n} x^{(0)}(k) - (n-1) \times \sum_{k=2}^{n} z^{(1)}(k)x^{(0)}(k)}{(n-1)\sum_{k=2}^{n} z^{(1)}(k)^2 - \big(\sum_{k=2}^{n} z^{(1)}(k)\big)^2} \tag{7}$$

$$b = \frac{\sum_{k=2}^{n} x^{(0)}(k) \times \sum_{k=2}^{n} z^{(1)}(k^2) - \sum_{k=2}^{n} z^{(1)}(k) \times \sum_{k=2}^{n} z^{(1)}(k)x^{(0)}(k)}{(n-1)\sum_{k=2}^{n} z^{(1)}(k)^2 - \big(\sum_{k=2}^{n} z^{(1)}(k)\big)^2} \tag{8}$$

The time response sequence of the GM(1,1) model in the Eq.(3) is given below

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, \qquad k = 1, 2, \cdots, n \tag{9}$$

The parameters $(-a)$ and b of the GM(1,1) model are referred to as the development coefficient and Grey action quantity, respectively. The former reflects the development states of $\hat{x}^{(1)}$ and $\hat{x}^{(0)}$. In general, the variables that act upon the system of interest should be external or pre-defined. Because GM(1,1) is a model constructed on a single sequence, it uses only the behavioral sequence (or referred to as output sequence or background values) of the system without considering any externally acting sequences (or referred to as input sequences, or driving quantities). The Grey action quantity in the GM(1,1) model is derived from the background values. It reflects changes contained in the data, and its exact intention is Grey. This quantity realizes the extension of the relevant intention. Its existence distinguishes Grey systems modeling from general input-output modeling. It is also a vital test stone of separating the thoughts of Grey systems and those of Grey boxes.

2.2 Valuation performance

Regarding the valuation performance of the volatility model for forecasting, there are some common approaches. This study adopted precipitation to evaluate the performance of the Grey rainfall forecasting model [8]. Model characteristics include periodicity, randomness, and tendency. To get the trend of the series and the context of the development of the natural disasters, this study, apart from improving the background value by integrating, has improved the accuracy by correcting the model's periodical errors. The MAPE is defined as follows

$$MAPE = \frac{100\%}{n} \sum_{k=2}^{n} \left| \frac{x_{(k)}^{(0)} - \hat{x}_{(k)}^{(0)}}{x_{(k)}^{(0)}} \right|, \tag{10}$$

where $x_{(k)}^{(0)}$ and $\hat{x}_{(k)}^{(0)}$ is the actual value and forecast one in time period k, respectively. The grade of MAPE is devided into four levels.

Table 1. The grade of MAPE

MAPE	**≤10%**	**10%-20%**	**20%-50%**	**≥50%**
Grade levels	Excellent	Good	Qualified	Unqualified

Second, the error of total cumulative rainfall (ETCR) is defined as

$$ETCR = \frac{\left| \sum_k^n x_{(k)}^{(0)} - \sum_k^n \hat{x}_{(k)}^{(0)} \right|}{\sum_k^n x_{(k)}} \tag{11}$$

A more accurate forecast can be obtained when ETCR is approximately zero. Third, the relative root means square error (RMSE) is defined as

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}\left[\left(x_{(k)}^{(0)} - \hat{x}_{(k)}^{(0)}\right)/x_{(k)}^{(0)}\right]^2}{n}} \tag{12}$$

A more accurate forecast can be obtained when RMSE is approximately zero. Fourth, the coefficient of efficiency (CE) is defined as

$$CE = 1 - \frac{\sum_{k=1}^{n}\left(x_{(k)}^{(0)} - \hat{x}_{(k)}^{(0)}\right)^2}{\sum_{k=1}^{n}\left(x_{(k)}^{(0)} - \bar{x}_{(k)}^{(0)}\right)^2} \tag{13}$$

Moreover, the coefficient of correlation (CC) is defined as

$$CC = \frac{\sum_{k=1}^{n}\left(x_{(k)}^{(0)} - \hat{x}_{(k)}^{(0)}\right)\left(\hat{x}_{(k)}^{(0)} - \bar{x}_{(k)}^{(0)}\right)}{\sqrt{\sum_{k=1}^{n}\left(x_{(k)}^{(0)} - \bar{x}_{(k)}^{(0)}\right) \times \sum_{k=1}^{n}\left(\hat{x}_{(k)}^{(0)} - \bar{x}_{(k)}^{(0)}\right)}} \tag{14}$$

3 Results and Discussion

Agriculture production in Vietnam is highly dependent upon precipitation, which falls in the form of rain. We used GM(1,1) model for predicting the real value of rainfall in Vietnam based on precipitation data from 2017 to 2020. The data were collected from fifteen meteorological regions located throughout Vietnam. These meteorological regions include 6 ones in the North (Lai Chau, Son La, Tuyen Quang, Ha Noi, Quang Ninh, Nam Dinh), 4 ones in the Central (Vinh, Hue, Da Nang, Quy Nhon), 2 ones in the Highland (Pleiku, Da Lat), and 3 ones in the South (Nha Trang, Vung Tau, Ca Mau). An explanation follows.

The sequence of raw data $X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), x^{(0)}(4)\right) = (2618.7,$ 2656.6, 2267.2, 2295.1) simulate the original sequence $X^{(0)}$ by respectively using the following three GM(1,1) models and compare the simulation accuracy:

From Eq.(3), we compute the accumulation generation of $X^{(0)}$ as follows $X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), x^{(1)}(4)\right) = (2618.7, 5275.3, 7542.5, 9837.6)$.

We check the quasi-smoothness from the class ratio $\sigma^{(1)}(k) = \frac{x^{(0)}(k)}{x^{(1)}(k-1)}$, it follows that $\sigma^{(1)}(2) = 0.503$, $\sigma^{(1)}(3) = 0.301$, $\sigma^{(1)}(4) = 0.233$. So, the condition to satisfy for $k > 3$, $\sigma^{(1)}(k) \in [0.5; 1]$ with $\sigma = 0.5$ and it is sufficient and necessary condition to ensure that the accumulate generating opera-tion (AGO) algorithm coverges. This result is the main contribution of grey class ratio. It not only makes the grey prediction model smooth, but also increases the accuracy of predicted values. Hence, according to above, mentioned result, it is concluded that the criteria which is derived in this section is reasonable formula and can be widely used in the field of GM (1,1) file. The law of quasi-exponentially the condition of quasi-smoothness is stratified. Thus, we can establish a GM(1,1) model for $X^{(1)}$. Let $Z^{(1)} = \left(z^{(1)}(1), z^{(1)}(2), \cdots, z^{(1)}(n)\right)$ be the sequence generated from $X^{(1)}$ by the adjacent neighbor means sequence

$Z^{(1)} = \left(z^{(1)}(1), z^{(1)}(2), z^{(1)}(3), z^{(1)}(4)\right) = (3947,\ 6408.9,\ 8690.05)$. In addition, matrix B constant vector Y_N are accumulated as follows

$$B = \begin{bmatrix} -3947 & 1 \\ -6408.9 & 1 \\ -8690.05 & 1 \end{bmatrix}, \tag{15}$$

$$Y_N = \begin{bmatrix} 2656.6 \\ 2267.2 \\ 2295.1 \end{bmatrix} \tag{16}$$

.

By using the least square estimation, we obtain the sequence of parameters $\hat{a} = [a, b]^T$. Then we use (7) and (8) to calculate the parameter:

* $a = \frac{19045.95 \times 7218.9 - (4-1) 44960392.035}{(4-1) \times 132169777.2125 - (19045.95)^2} = 0.0772$
* $b = \frac{7218.9 \times 132169777.2125 - 19045.95 \times 44960392.035}{(4-1) \times 132169777.2125 - (19045.95)^2} = 28970.31$

Then $\hat{a} = (B^T B)^{-1} B^T Y = \begin{bmatrix} 0.0772 \\ 2897.03 \end{bmatrix}$, hence we find values of a=0.0772 and b=28970.31.

We establish the following model $\frac{dx^{(1)}}{dt} - 0.00768x^{(1)} = 399.433$ and building the prediction equation time response form $\hat{x}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k)} + \frac{b}{a} = -34908e^{-0.772} + 37526.3$. Substitute different values of k into the equation

* $k = 1X^{(1)}(1) = 2618.7$
* $k = 2X^{(1)}(2) = 5211.8$
* $k = 3X^{(1)}(3) = 7612.1$
* $k = 4X^{(1)}(4) = 9833.7$
* $k = 5X^{(1)}(5) = 11890.1$
* $k = 6X^{(1)}(6) = 13793.6$
* $k = 7X^{(1)}(7) = 15555.4$
* $k = 8X^{(1)}(8) = 17186.3$

Compute the simulated values of $X^{(0)}$ the original series according to the accumulated generating operation of by using $\hat{x}^{(0)}(k+1) = \alpha^{(1)}\hat{x}^{(01)}(k+1) - \hat{x}^{(1)}(k)$:

* $X^{(0)}(1) = x^{(1)}(1) = 2618.7$ forecast for the year 2017
* $X^{(0)}(2) = x^{(1)}(2) - x^{(1)}(1) = 2593.1$ forecast for the year 2018
* $X^{(0)}(3) = x^{(1)}(3) - x^{(1)}(2) = 2400.2$ forecast for the year 2019
* $X^{(0)}(4) = x^{(1)}(4) - x^{(1)}(3) = 2056.4$ forecast for the year 2020
* $X^{(0)}(5) = x^{(1)}(5) - x^{(1)}(4) = 1903.4$ forecast for the year 2021
* $X^{(0)}(6) = x^{(1)}(6) - x^{(1)}(5) = 1761.8$ forecast for the year 2022
* $X^{(0)}(7) = x^{(1)}(7) - x^{(1)}(6) = 1630.8$ forecast for the year 2023
* $X^{(0)}(8) = x^{(1)}(8) - x^{(1)}(7) = 1630.8$ forecast for the year 2024

This study is concerned with the metrics that can accurately reflect the rainfall measurement during the period 2017 - 2020. According to Ho et al., the MAPE is to identify the Grey prediction models with good performance; the ETCR and RMSE represent a quantitative judgment of model performance [5]. The CE is used to measure the similarity between the predicted and observed accumulated rainfall. The CC is used to measure the correlative relationship between the predicted and observed accumulative rainfall. When we use the above computation process, we could get the forecasting results of all the 15 regions from 2021 to 2024. The detailed results are shown in Table 3 and Table 3.

Table 2. The grade of Average MAPEs rainfall of meteorological regions in Vietnam

	ETCR	**RMSE**	**CE**	**MAPE**	**CC**
Lai Chau	0.000397	0.035485	0.788485461	0.21%	0.2927
Son La	0.000789	0.069285	0.516938651	0.16%	0.0571
Tuyen Quang	0.003096	0.100293	0.645361493	0.41%	0.08
Ha Noi	0.000838	0.013321	0.98	0.42%	0.0697
Quang Ninh	0.000662	0.12145	0.279955058	0.36%	0.212
Nam Dinh	0.000525	0.045339	0.822012083	0.33%	0.0632
Vinh	0.006107	0.116268	0.824307146	0.24%	0.0802
Hue	0.000741	0.024885	0.911553061	0.06%	0.2791
Da Nang	0.00048	0.026752	0.948342121	0.23%	0.112
Quy Nhon	0.001358	0.006221	0.997702553	0.16%	0.0592
Pleiku	0.0003	0.101836	0.479397367	0.36%	0.1417
Da Lat	8.08E-07	0.027265	0.507316817	0.45%	0.0981
Nha Trang	0.000166	0.165978	0.518417604	0.28%	0.0474
Vung Tau	5.57E-05	0.016562	0.885136372	0.25%	0.045
Ca Mau	0.000543	0.009087	0.978981993	0.25%	0.0987
Average	**0.0011**	**0.059**	**0.739**	**0.00%**	**0.116**

Table 3 shows that several requirements of the model accuracy are met such as residual error (MAPE): 0.0038%, ETCR: 0.0011, RMSE: 0.059, CE: 0.73, and CC: 0.116. The above statistics confirm the efficiency of the proposed forecasting model that the average residual error was smaller than 10%. This result means the forecasting process is excellent, so it strongly confirms that the GM(1,1) model provides a highly accurate prediction. Therefore, we select MAPE to calculate the error for this rainfall forecast model in this study. Then the results of rainfall prediction using the Grey forecasting method are presented in Table 3 below.

As shown in Table 3, among the 15 regions, 5 regions, which are Son La, Tuyen-Quang, Da Lat, Nha Trang and Ca Mau, are expected to have annual rainfall increase through the upcoming 4 years. Tuyen Quang province will have the highest increase of rainfall, followed by Ca Mau province and Son La province. While the 10 remaining regions will suffer from a significant decrease of rainfall

Table 3. Forecast of rainfall in Vietnam from 2021 to 2024

	2021	**2022**	**2023**	**2024**	**Gap between 2024 and 2021**
Lai Chau	2056.416	1903.449	1761.861	1630.805	-425.611
Son La	1883.146	2055.677	2244.016	2449.609	566.463
Tuyen Quang	2411.015	2828.856	3319.11	3894.327	1,483.31
Ha Noi	1324.904	1171.5	1035.858	915.922	-408.982
Quang Ninh	1972.19	1814.269	1668.994	1535.351	-436.839
Nam Dinh	1253.402	1109.251	981.677	868.776	-384.626
Vinh	929.731	680.012	497.367	363.778	-565.953
Hue	1928.086	1727.516	1547.81	1386.799	-541.287
Da Nang	1737.015	1568.951	1417.148	1280.032	-456.983
Quy Nhon	1146.694	967.825	816.857	689.438	-457.256
Pleiku	1608.518	1408.192	1232.814	1079.279	-529.239
Da Lat	2004.291	2012.19	2020.119	2028.08	23.789
Nha Trang	1361.24	1413.866	1468.527	1525.301	164.061
Vung Tau	1257.412	1217.769	1179.377	1142.194	-115.218
Ca Mau	2484.71	2706.104	2947.225	3209.831	725.121

until 2024. Nota-bly, Vinh city will experience the biggest shortage of rainfall as the predicted rainfall in 2024 will be approximately one third of that in 2021.

The estimated rainfall volume in the period from 2021 to 2024 of these 15 regions will serve as an important input for farmers and the governing agencies in agriculture sector to formulate contingency plans to leverage the risks of rainfall fluctuation.

4 Conclusion

Quantitative precipitation forecast (QPF) is one of the most important issues for the meteorological community. Many efforts had been spent on analyzing the capability of the numerical model in providing QPF. For example, Emerton et al. evaluated the performance of the Regional Spectral Model (RSM) developed at the National Centers for Environmental Prediction (NCEP) in providing quantitative precipitation forecasts for the Tennessee and Cumberland River Watersheds, USA [3]. They found that the model's performance was more accurate than the traditional forecasting models. However, the QPF performance of RSM for Williamson was relatively unsatisfactory [10].

This study modified an integrated framework for the rainfall forecasting model using a real-time flow updating algorithm. Applying GM(1,1) to forecast short-term rainfall growth rates can achieve excellent prediction. GM(1,1) can estimate the residual values and then use MAPE, RSME, CE, and CC to calculate the valuation performance. The result of this study is essential in forecasting the natural disasters risk index. It may be concluded that effective rainfall is directly proportional to consumptive use, water storage capacity, irrigation application and seepage and percolation losses. Policymakers may use these results to formulate suitable policies towards a sustainable agriculture sector. The prediction in this study indicates that the applied Grey model process will help the small farming households reduce the risks and gain benefits from seasonal forecasts of the rainfall.

This study still has some limitations. Daily and monthly precipitation data in Vietnam are not available so that we cannot compute the expected rainfall on the daily or monthly basis. We have just estimated the total rainfall amount in a year, but have not predicted the amount of rainfall for each month or each day. For future studies, we may apply different forecasting models that can be used to optimal forecasting value of the rainfall and also other natural disasters risk index in the future.

References

1. Brémaud, P., Pointin, Y.: Forecasting heavy rainfall from rain cell motion using radar data. Journal of hydrology **142**(1-4), 373–389 (1993). https://doi.org/https://doi.org/10.1016/0022-1694(93)90019-6
2. Deng, J.: Introduction to grey system theory. The Journal of Grey System **1**(1), 1–24 (1989)
3. Emerton, R.E., Stephens, E.M., Pappenberger, F., Pagano, T.C., Weerts, A.H., Wood, A.W., Salamon, P., Brown, J.D., Hjerdt, N., Donnelly, C., et al.: Continental and global scale flood forecasting systems. Wiley Interdisciplinary Reviews: Water **3**(3), 391–418 (2016). https://doi.org/https://doi.org/10.1002/wat2.1137
4. Hansen, J.W., Mishra, A., Rao, K., Indeje, M., Ngugi, R.K.: Potential value of GCM-based seasonal rainfall forecasts for maize management in semi-arid kenya. Agricultural Systems **101**(1-2), 80–90 (2009). https://doi.org/https://doi.org/10.1016/j.agsy.2009.03.005
5. Ho, J.Y., Lee, K.T.: Grey forecast rainfall with flow updating algorithm for real-time flood forecasting. Water **7**(5), 1840–1865 (2015). https://doi.org/https://doi.org/10.3390/w7051840
6. Jones, J.W., Hansen, J.W., Royce, F.S., Messina, C.D.: Potential benefits of climate forecasting to agriculture. Agriculture, ecosystems & environment **82**(1-3), 169–184 (2000). https://doi.org/https://doi.org/10.1016/S0167-8809(00)00225-5
7. Lee, C.S., Huang, L.R., Shen, H.S., Wang, S.T.: A climatology model for forecasting typhoon rainfall in taiwan. Natural Hazards **37**(1-2), 87–105 (2006). https://doi.org/10.1007/s11069-005-4658-8
8. Lin, Y.H., Chiu, C.C., Lee, P.C., Lin, Y.J.: Applying fuzzy grey modification model on inflow forecasting. Engineering Applications of Artificial Intelligence **25**(4), 734–743 (2012). https://doi.org/https://doi.org/10.1016/j.engappai.2012.01.001
9. Purdy, J.C., Harris, D., Austin, G.L., Seed, A.W., Gray, W.: A case study of orographic rainfall processes incorporating multiscaling characterization techniques. Journal of Geophysical Research: Atmospheres **106**(D8), 7837–7845 (2001). https://doi.org/https://doi.org/10.1029/2000JD900622
10. Williamson, S., et al.: Pesticide provision in liberalised africa: out of control? (2003)