Optimal evacuation decision policies for Benue flood disaster in Nigeria

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Abstract. This research develops a probabilistic evacuation decision policy model to determine the optimal decision for the cases of no evacuation, evacuation, and delay decision at a particular point in time in the event of a threatening flood disaster adapted to the case of Nigeria. This work explores the use of decision tree analysis and a program written in MATLAB to solve problems arising from the models to determine the optimal decision. An application to the case of Benue flood 2012 reveals that earlier evacuation would have saved the decision-maker (government) almost 4-times less than the cost incurred after evacuation was initiated at later time.

Keywords: optimal evacuation; decision policy; flood; disaster; economic planning

1. Introduction
Decision making in the face of threatening disaster is a strong tool in disaster management. Taking into consideration the consequences of every decision made at any particular period of time that there is a threatening disaster, it is crucial that a decision that seeks to maximize benefits and minimize loss be made by a decision-maker. Doing this requires more than intuitive response. Hence, the motivation for this research that seeks to determine the optimal (the decision with most preferred consequence) evacuation decision policies for disaster: a case of Benue flood 2012.

Flood is referred to as an overflow of large amount of water covering a place or land; such land is ordinarily of dry nature [1]. Flood is also defined as large volume of water occupying the stream channel and plain damaging the economic activities and valuables therein [2]. Flood is a serious environmental issue (whenever it occurs), it affects both urban and rural areas likewise natural resources and the economy [3-5]. In Nigeria, these damaging syndromes such as windstorms, unadorned flood, drought, climate factors and so on have indeed recorded adverse effects on the socio-economy activities of the country [6].

Frequent occurrence of flood in the nation has revealed that flood is the most common disaster in Nigeria. During the raining season, most of the larger river plains in the country experience severe flooding. Some of these areas are Cross River, Rivers Niger, Katsina, Imo, and Benue. Different parts
of the nation have had their portions of the flood disaster in the recent times. The impact of the recent major flooding in the states has really increased the awareness of both the government and individuals on how deadly flood disaster could be. The country has it in record that the 2012 flood disaster has been the most deadly of all flooding the nation has ever experienced. Below is the record of the recent time flooding across the nation.

2. Nigeria—Most recent flood disaster and impact
   The year 2012 marked the year Nigeria recorded her worst flooding like never before. According to the National Emergency Management Agency, the flood which lasted from July 1 to October 31, 2012, claimed the lives of 363 people and 18,282 people were treated for injuries sustained during the flooding. Also, a total of 7.7 million people were affected during the period, of which 2.1 million were officially registered across the country as internally displaced persons (IDPs). Almost 600,000 houses had been damaged and many farmlands were swept away by the flood. The flood affected most of the food producing states like Benue, Kogi, etc., thereby increasing food crisis in the country.

   In all, the flood left nine states across the country submerged. The states include Bayelsa, Delta, Edo, Benue, Cross River, Anambra, Kogi, Kwara and Niger. Some other states also had the taste as the flood swept few communities and local governments in these states. These states include Kano, Adamawa, etc.

   The flood has been as a result of heavy rainfall which increased the water level of the plateau, the rivers and the Ladgo dam in Cameroun. Notably, the release of excess water from Ladgo dam to avert the collapse of the dam contributed immensely to the more fatal effect of the flood emerging in the neighbouring states. The major flood disaster in the nation has cost the federal government NGN17.6 billion. Meanwhile the Presidential Committee on Flood Relief and Rehabilitation led by [7] realized more than NGN11.35 billion in cash and promissory donations for victims of flood across the country (Premium Times, Nov. 9, 2012).

   The cost of evacuation and damage would not have been that much if evacuation had been initiated (it could be forceful evacuation by the government) before the hit of the disaster. According to the Delta State Technical Committee on Flood Impact Assessment [8], farmlands, buildings and livestock that were destroyed in the various communities. The impact on crops was put at NGN3.1 billion, while that of livestock at NGN2.5 billion. In all, tangible property damaged by flood amount to NGN9.602 billion. The committee said its reversed estimate for building a mud house is NGN100,000, while a block house is NGN2.2 million.

   However, evacuation would not always be the optimal decision to make as the forewarned disaster may fail to occur. Such are few cases in Lagos where a high-water level was predicted and evacuation warning issued to the residents but the predicted increase in water level would not later lead to flood. In such cases, the decision to evacuate will end up being a mere loss to the decision-maker, since no damage would have been incurred if he has stayed back. This forms part of the motivation into this research.

   The main reason to call for evacuation of residents at risk in Nigeria in 2012 was the expected high rainfalls which could lead to flood as foreseen by NIMET. Currently a decision regarding evacuation is established on a deterministic criterion (looking at the condition of wetter-than-normal) and experience (judgment on the weather conditions by the experts).

2.1. Overview of Evacuation Phases
   This work explores the use of decision tree analysis to determine the optimal decision and also determined probabilities of flooding gathered from data of previous occurrences.

   Kolen [10], considers a probabilistic evacuation model to determine expected loss of Life for different strategies for mass evacuation. Czajkowski [11], considers some limitations to the known hurricane evacuation modeling. Other researches on evacuation decisions include those of [12, 13].
2.2. Standardized Precipitation (SP) Index

The Standardized Precipitation (SP) Index indicates a probability index that yields a better representation of abnormal dryness and/or wetness than the usual Palmer Severe Drought (PSD) Index. The SP index is gotten by fitting a gamma or a Pearson Type III distribution to the values of monthly precipitation [14]. The SP index in June 2012, showed extremely wet and wet conditions in the specified areas coloured blue and green respectively in Figure 1. Thus, guaranteed sufficient lead time to give updates for the peak of the rainy season viz: July, August and September. Figure 1 shows the map of the, 6-month and SPIs. Figure 2 shows the deviation of the predicted and the observed 2012 seasonal rainfall amount.

In 2012, the prediction of rainfall amount was normal-to-above normal. Meanwhile, the released update in early July 2012 predicted clearly that excessive flooding and rainfall were very likely to occur during the months of July, August and September 2012 in many parts of the country.

Population growth and development of any nation with regard to welfare, human right valuation, properties, and security ought not be neglected [15-20].

3.0 Parameters of the model and effects of timing

In the evacuation decision model, potential flood damage (which is considered increasing with a decreasing lead-time) and evacuation costs (which is considered decreasing with a decreasing lead time is observed in Figure 2.

Figure 1: Prediction from the observed 2012 seasonal rainfall amount (6-months SPI)

Deviation of the predicted observed 2012 seasonal rainfall amount lead-time will be considered.
3.1. Evacuation decision criterion

In these models, the decision-maker must decide whether to stay “No Evacuation” or “Evacuation”. We assume the decision to evacuate is irreversible in the sense that, the decision-maker may decide to evacuate at a later time. We also assume that the prediction is certain probability of flooding.

3.2. One-period evacuation decision model

Given the water level or expected high rainfall, ‘flooding’ (event \( \Theta_1 \)) is forecast to happen with probability \( p_{\text{flooding}} \) and (event \( \Theta_2 \)) for ‘no flooding’ such that \( 1 - p_{\text{flooding}} \) signifies the associated complementary probability. Let \( \{a_{1,1}, a_{1,2}\} \) be the set feasible decisions for \( a_{1,1} \) corresponding to ‘no evacuation’, \( a_{1,2} \) to ‘evacuation’, and the term \( d \) consisting of a smaller number of fatalities, including people of whom the evacuation failed. The presumed costs of decision \( a_{1,1} \) and \( a_{1,2} \) are defined as:

\[
E(a_{1,1}) = p_{\text{flooding}} \cdot d. \\
E(a_{1,2}) = p_{\text{flooding}} \cdot d + C. 
\]

The optimal cost of decision at \( t_i, OD_i \), we have:

\[
OD_i = \min \left[ E(a_{1,1}), E(a_{1,2}) \right]. 
\]

As such, on the basis of presumed costs minimization, a decision-personnel decide to evacuate the risk area at \( t_i \) if:

\[
E(a_{1,1}) > E(a_{1,2}).
\]

Substituting equations (1) and (2) in (4) we obtain:

\[
p_{\text{flooding}} \cdot D, p_{\text{flooding}} \cdot d + C.
\]
\[ p_{f|\text{pred}}(D-d) > C. \]

Equation (6) helps to distinguish between the benefits and the costs of an evacuation. The left-hand side of (6) gives the sum of the benefits, and the right-hand side gives the sum of the costs. Not meeting (4) shows a non-optimal evacuation decision at \( t_i \).

3.3. Two-period evacuation decision model

In the evacuation decision criterion, the chances delaying the evacuation need to be considered. As earlier stated, the decision to evacuate will be considered irreversible while the decision not to evacuate is reversible. The corresponding tree is shown in Figure 3.

Figure 3: Evacuation decision tree for Two-period

At \( t = t_i \) (now) the decision-maker is notified via information received that a predicted high water level or high rainfall, \( h_{\text{pred}} \), could engulf a low-lying area in future time at \( t = t_0 \). Moreso, the decision-maker knows that more information flood will be received at a later stage at time \( t = t_i \) between \( t_i \) and \( t_0 \) signifying predicted flood movement.

In the sequel, let \( p_{f|\text{pred}}(t_i, t_j) \) (resp. \( 1 - p_{f|\text{pred}}(t_i, t_j) \)) be the probability of flooding (resp. no flooding) for the events \( \theta_1 \) (resp. \( \theta_2 \)) at time \( t \), then, the two-period evacuation decision tree is considered from the right side (RHS) to the left (LHS) with the presumed costs of decision \( a_{j,1} \) for no evacuation at \( t_j \) given as:

\[
E(a_{j,1}) = p_{f|\text{pred}}(t_i, t_j) \cdot D.
\]

The presumed costs of decision \( a_{j,2} \) (evacuation) at \( t_j \) are given by:

\[
E(a_{j,2}) = p_{f|\text{pred}}(t_i, t_j)(c + d^*) + (1 - p_{f|\text{pred}}(t_i, t_j)) \cdot c = p_{f|\text{pred}}(t_i, t_j) \cdot d^* + c.
\]

The optimal cost of decision at \( t_j \) denoted as \( OD_j(t_j) \) is obtained by the minimization of the total presumed costs.
\( OD_j (t_j) = \text{Min} \left[ E \left( a_{j,1} \right), E \left( a_{j,2} \right) \right]. \) (9)

The expected (presumed) costs of decision \( a_{i,1} \) (no evacuation) at \( t_j \) is determined by the optimal cost of decision at \( t_j \) \((OD_j (t_j))\), resulting in:

\[
E \left( a_{i,1} \right) = OD_j (t_j) = \text{Min} \left[ E \left( a_{j,1} \right), E \left( a_{j,2} \right) \right].
\] (10)

The presumed costs of decision \( a_{i,2} \) at \( t_i \) yields:

\[
E \left( a_{i,2} \right) = p_{f_{i\text{pred}}} (t_i, t_i) * (C + d) + \left( 1 - p_{f_{i\text{pred}}} (t_i, t_i) \right) * C \\
= p_{f_{i\text{pred}}} (t_i, t_i) * d + C.
\] (11)

For the total presumed costs minimization, the optimal cost of decision at \( t_i \) is given by:

\[
OD_i (t_i) = \text{Min} \left[ OD_j (t_j), E \left( a_{i,2} \right) \right].
\] (12)

An ideal decision-personnel evacuates the area at \( t_i \) if:

\[
\begin{align*}
E \left( a_{i,1} \right) &> E \left( a_{i,2} \right) \\
\text{or} \\ OD_j (t_j) &> E \left( a_{i,2} \right).
\end{align*}
\] (13)

In some situation, the reversible decision parameter, \( a_{i,1} \) for no evacuation is considered.

### 3.4 Decision tree model for Multi-period Evacuation

These models are extension of the two-period evacuation decision model. Both models possess a maximal prediction lead time of 4 days. The details of the multi-period evacuation models are contained in [9].

Meanwhile, in Nigeria, the Gumbel (EV-1), Log Normal and Log Pearson Type III probability distribution models are used to predict flooding of rivers with little or no information about the average lead time of these models.

Handling the multi-period decision tree results in the optimal cost of decision at different time interval such that:

\[
t = t_1 : OD_1 (t_n) = \text{Min} \left[ E \left( a_{1,1} \right), E \left( a_{1,2} \right) \right],
\] (14)

where

\[
E \left( a_{1,1} \right) = p_{f_{i\text{pred}}} (t_n, t_i) * D.
\] (15)

\[
E \left( a_{1,2} \right) = p_{f_{i\text{pred}}} (t_n, t_i) * (C (t_i) + d (t_i)) + \left( 1 - p_{f_{i\text{pred}}} (t_n, t_i) \right) * C (t_i) \\
= p_{f_{i\text{pred}}} (t_n, t_i) * d (t_i) + C (t_i).
\] (16)

According to (10), we havethat:

\[
E \left( a_{2,1} \right) = OD_1 (t_n) \\
= \text{Min} \left[ E \left( a_{1,1} \right), E \left( a_{2,1} \right) \right].
\] (17)

where \( E \left( a_{2,1} \right) \) is the presumed costs of decision \( a_{2,1} \) (no evacuation) at \( t_2 \). So that at:

\[
t = t_2 : OD_2 (t_n) = \text{Min} \left[ OD_1 (t_n), E \left( a_{2,2} \right) \right]
\] (18)
where \( E(a_{2,2}) \), the presumed costs of decision \( a_{2,2} \) (evacuation) at \( t_2 \) amount to:

\[
E(a_{2,2}) = p_{\text{f|pred}}(t_n, t_2) \cdot (C(t_2) + d(t_2)) + (1 - p_{\text{f|pred}}(t_n, t_2)) C(t_2)
\]

Continuing in this manner, we obtain \( E(a_{n-1,2}) \) and \( E(a_{n,2}) \), the presumed costs of decision \( a_{n-1,2}, a_{n,2} \) (evacuation) at \( t_{n-1} \) and \( t_n \) respectively amount to:

\[
E(a_{n-1,2}) = p_{\text{f|pred}}(t_n, t_{n-1}) \cdot d(t_{n-1}) + C(t_{n-1})
\]

\[
E(a_{n,2}) = p_{\text{f|pred}}(t_n, t_n) \cdot d(t_n) + C(t_n).
\]

Also, continuing in the manner of (17) we obtain:

\[
E(a_{n,1}) = OD_{n-1}(t_n)
\]

where \( E(a_{n,1}) \) is the presumed costs of decision \( a_{n,1} \) at \( t_n \) for no evacuation. Continuing in the manner of equation (18) we have at:

\[
t = t_{n-1}, OD_{n-1}(t_n) = \min\left[ OD_{n-2}(t_n), E(a_{n-1,2}) \right],
\]

\[
t = t_n, OD_n(t_n) = \min\left[ OD_{n-1}(t_n), E(a_{n,2}) \right].
\]

In general term, the equation for the optimal cost of decision at different time frame in the decision tree is given as:

\[
\min_{j=2}^{n} \left[ OD_{j-1}(t_j), E(a_{j,2}) \right].
\]

Equation (25) cannot be applied to find the optimal cost of decision at \( t_j \) \((j = 1)\), \( OD_1(t_j) \), because a value for \( OD_0(t_j) \) cannot be obtained. For \( OD_1(t_j) \), the next equation is applied:

\[
OD_1(t_j) = \min\left[ E(a_{1,1}), E(a_{1,2}) \right].
\]

In general, a decision personnel (maker) will choose to evacuate the area at \( t_j \) if the decision to evacuate is optimal if:

\[
E(a_{j,1}) > E(a_{j,2})
\]

or

\[
OD_{j-1}(t_n) > E(a_{j,2}), (1 \leq j \leq n).
\]

We make reference to Figure 4 for multi-period evacuation decision tree.
4. Application/Case study

In the application of this decision tree model developed, to the case study of Benue flood disaster 2012, a Three-Period evacuation decision tree will be used to evaluate the optimal evacuation decision. In the development of the problem here, it is assumed that there are three (3) stages of decision-making and that at stage 1 and stage 2, the decision-maker (Nigerian Government) has chosen the decision “No Evacuation” not until the last stage.

The data retrieved from the internet source will be applicable to the evacuation costs and flood damage at stage 3 only. Meanwhile, the cost of evacuation, and flood damage at stages 1 and 2 will be assumed based on the assumption of the model (i.e evacuation costs decrease with decreasing lead time and flood damage increases with decreasing lead time). This problem also assumed that at the stage when evacuation was made by the decision-maker, it was already certain that there was flood (thus the probability at stage 3 is taken to be 1). Meanwhile, probabilities of flooding at stages 2 and 1 are chosen to be 0.8 and 0.4 respectively since it is assumed that at stage 1 heavy rainfall has begun even before the Lado dam release which increased the effect.

It was gathered that the disaster cost the federal government 17.6 billion naira and the Presidential Committee on Flood Relief and Rehabilitation led by Dangote [7] realized more than 11.35 billion naira in cash and in promissory donations for victims. This sum is used as evacuation costs in this problem.

Monetary Value of a human life in Nigeria, $MVHL_N$, is estimated as follows (where $ALExp$ denotes average life expectancy, and NGN = Naira):

$$MVHL_N = \frac{NNP}{Total \ Population} \times (ALExp) = USD \ 1,548,311.$$  \hspace{1cm} (28)

Gathered from newspaper, 363 people were dead and 2.1 million people registered as internally displaced persons (IDPs).

Loss of life is therefore estimated at NGN87.7 million. The total of (2.1 million + 363) people will be used as valued for human damage if no evacuation had not been made at all. This amounts to 507,386.51 million naira damage.

Figure 5 gives the summary of the flood damage and evacuation costs.
Evacuation Costs = NGN17.6billion + NGN11.35billion = NGN28.95 billion.

Using these data, the problem is thus solved in the decision tree (see Figure 5) via (14) through (24) as indicated at the nodes. Hence, the optimal decision at time $t_1$ is ‘Evacuation’. Since the assumption is that the decision to evacuate is irreversible, then we conclude that, in the case study of Benue flood 2012, earlier evacuation immediately before the heavy rainfall met with the Ladgo dam release would have been the optimal decision with the optimal expected cost estimated at NGN177.31billion. This optimal expected cost when compared with the flood damage, it is 3 times less than the flood damage incurred. A program written in MATLAB is used for the solution of the Three-Period Evacuation Decision Tree.

Figure 5: Application of three-period evacuation decision model to the case study

Table 1: Damages

| Livestock Household Affected Human loss Crops | NGN54,222.924m billion | NGN458,865 million |
|---------------------------------------------|------------------------|-------------------|
|                                             | NGN87.7 million        | NGN81,778.925 million |

If no evacuation had not been made at all, the total damage is estimated at: NGN594,954.549million + (monetary value of 2.1million internally displaced persons that would have been dead).

\[
\text{The estimate} = 594,954.549 + 2,100,000 = 595,054,549 \text{ million}.
\]

Using these data, the problem is thus solved in the decision tree (see Figure 5) via (14) through (24) as indicated at the nodes. Hence, the optimal decision at time $t_1$ is ‘Evacuation’. Since the assumption is that the decision to evacuate is irreversible, then we conclude that, in the case study of Benue flood 2012, earlier evacuation immediately before the heavy rainfall met with the Ladgo dam release would have been the optimal decision with the optimal expected cost estimated at NGN177.31billion. This optimal expected cost when compared with the flood damage, it is 3 times less than the flood damage incurred. A program written in MATLAB is used for the solution of the Three-Period Evacuation Decision Tree.

\[
\text{The estimate} = 594,954.549 + 2,100,000 = 595,054,549 \text{ million}.
\]
5. Conclusions

In this paper, the rational evacuation decision model (EDM) is applied to the Benue flood disaster case of 2012. Evacuation was initiated in later time when it was obvious that the flood damage to the economy was already irrecoverable and only human beings became the objects to be evacuated. Meanwhile, most other valuables could not be recovered for evacuation. Though, the evacuation made was intuitively initiated but the results from the rational evacuation decision model show that earlier evacuation would have saved the decision-maker about 4- times less than the total evacuation cost incurred.

The rational EDM can be implemented in Nigeria, if the flood predictions were more accurate (including probabilities of flooding) and the economic damages included in the evacuation costs and potential flood damage. This research recommends the following:

(i) Nigerian Meteorological Agency (NIMET) should engage the experts in the area of Operations Research in further research to model the probability of occurrence of event of flooding given that it is predicted.

(ii) NIMET and National Emergency Management Agency (NEMA) should provide accessible-for-all information platform to communicate disaster predictions and warnings, ensuring regular updates of information up till the expiry of the lead-time and including during evacuation.

(iii) The government through NEMA should put enough facilities in place for efficient evacuation process (i.e. disaster preparedness, warning, response and evacuation).

Conflict of interest
The authors declare that there exists no conflict of interest regarding the publication of this paper.

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