A MODEL TO SIMULATE RAINFALL FOR BANGLADESHI SUSTAINABLE AGRICULTURE

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***Abstract*—To replicate the yearly fluctuation in rainfall amount that is seen in Bangladesh, a simulation model for rainfall depending upon a first-order Markov chain has been created. In the Barind Tract in Bangladesh, where the technique has been tried, The original and simulated seasonal, yearly, and average monthly data barely differed much. An asymptotic normality test characterizes the success rates. No discernible change in rice production response was found when authentic and calculated regular rainfall records were utilized to power a crop simulation model. According to the findings, the rainfall simulation model is capable of handling a variety of tasks.**

***Index Terms*—Rainfall**

I. Introduction

Environmental change can have a significantly bigger influence on financially deprived farmers than its apparent likelihood of happening. Nearly the entire country of Bangladesh experiences droughts and flooding, varying in severity. In both the dry season (June) and the rainy season (Kharif), there are various levels of drought (Rabi). The drought had a significant impact on the T. Aman rice harvests during the Kharif season on an estimated 0.574–1.748 million hectares. Because of Bangladesh's heavy rainfall, floods happen. Such rainstorms, which last 3 to 10 days, resulting in massive flooding that harms agriculture and assets due to insufficient drainage systems. Simulation modelling approaches are being utilized more and more to build and evaluate agrotechnology that may be distributed to farmers as well as extrapolate the findings of field testing. This study provides a first-order Markov chain model-based simulation model for rainfall. Both the findings of the rainfall simulation model as well as the outcomes of the agriculture production simulation model are reported.

II. Methodology

A. The Rainfall Model:

The likelihood of a rainy day preceding a drier day and the chance of a drier day after a rainy day are two conditional possibilities that must be calculated when using a two-state Markov chain approach. The simulated model for rainfall was constructed utilizing a first-order Markov chain model. The model took as input the monthly probability of getting precipitation if the day before had been dry and the monthly possibilities if the day before had been rainy. Although the wet-dry percentages are unavailable, it is possible to infer them using the typical amount of rainy days.

$$P_j(W/D) = \beta \; \mathrm{d}p_j/\mathrm{d}m_j \qquad (1)$$

$$P_j(W/W) = 1 - \beta + P_j(W/D) \qquad (2)$$

In which Pj(W/D) is the possibility of a rainy day following a dry day in month j, Pj(W/W) is the possibility of a rainy day following a rainy day in month j, dp is the number of days with precipitation in month j, and Beta is equivalent to 0.75 for the scenario. Based on the initial wet-dry condition, the model probabilistically decides whether the rain will fall. The relevant wet-dry probabilities are evaluated to a randomly generated value (0–1) before being created. Rain falls on that day if the random value is lower than or equivalent to the wet-dry possibility. No rain is predicted by a random number larger than the wet-dry possibility. On days when rain falls, daily rainfall levels are calculated using a censored gamma distribution with a lower limit of 0.1 mm. Utilizing the solution, the quantity of rain that falls each day is derived from a distorted normally distributed.(Arnold et al., 1990).

$$R = \mu + 2\sigma/\beta[\{\beta/6 \; (z - \beta/6) + 1\}^3 - 1] \qquad (3)$$

wherein R is the daily average rainfall, Miu is the average magnitude of the rainfall event on a specific rainy day, Delta is the standard deviation, Beta is the skewed factor, and z is the standard deviation of the normal distribution. The Barind rainfall monitoring station's mm of measured rainfall by the Bangladesh Water Development Board is the source of the data utilized in this research. For climatological investigations, everyday time series analysis over a lengthy period of time is not accessible. But the research relies on simulated data, which is dependent on the data's accessibility. There should be 3 agro-climatic periods in Bangladesh: (1) before kharif (summer), which involves the months leading up to the monsoon (March to May); (2) kharif, which involves the monsoon months (June to October), during which 80

B. Tactic of maximal probability estimation:

Take into account the likelihood function, that is represented by

$$P_0 = \Pr\{W/D\} \quad (4)$$

$$P_1 = \Pr\{W/W\} \quad (5)$$

This series is a Markov chain with dual stochastic phases that is irreconcilable. An accomplishment is possible according to its stationary likelihood function.

$$P = P_0/1 - (P_1 - P_0) \quad (6)$$

For each attempt up to and including the following progress, the recurring time distribution of progress has probability P1, (1-P1)Po, (1-P1)(1-Po)Po. As a result, the average and range of recurring times are provided below:

$$\mu = \{1 - (P_1 - P_0)\}/P_0, \quad \sigma^2 = (1 - P_1)(1 + P_1 - P_0)/P_0^2 \quad (7)$$

Let S represent progress at this point. S is monotonically regularly distributed, which means

$$S \sim \mathrm{AND}(n/\mu, n\sigma^2/\mu^3) \quad (8)$$

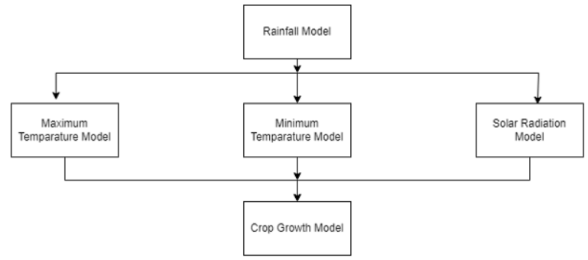
We are aware that when and is replaced,

$$E(S) = nP, \quad \mathrm{Var.}(S) = nP(1 - P)(1 + d)/(1 - d) \quad (9)$$

in which d-P1-Po. This represents an approximate finding that doesn't reveal either the precise distribution for small n or the speed at which things are approaching normalcy (Feller, 1957).

C. The model of growing crops:

A crop growth model and environment synthesizer have been included (Fig. 1). According to the EPIC model (Sharpley and Williams, 1990). The Barind Tract in Bangladesh has been used to evaluate the crop model (Rahman and Rushton, 2000). Crop models are only working hypotheses, and in scientific knowledge it is impossible to show a theory to be entirely accurate. Nevertheless, evaluating a model throughout various circumstances gives plenty of chance to pinpoint its flaws (Whisler et al., 1986). This is a daily step-operated simulation model of crop production and development. The dry stuff created by photosynthesis rate and the radiation it emits.



The plant cells which are developing at that moment on each given day are divided up. The aggregation of the daily thermal period governs the phenotypic expression of the crop. Temperatures at their highest and lowest points each day, precipitation, solar radiation factors, plant and management info, and soil data are all used as data sources. Rainfall has an impact on both temperature and radiation from the sun. Biomass has been predicted using the system in order to evaluate the diversity in these estimations and to pinpoint the major factors that influence the inaccuracy of the predictions. Latin Hypercube Sampling (LHS) assessment technique and the LHS/Partial Rank Correlation Coefficients (PRCC) scenario analysis have to be used due to the model's complicated structural makeup and the high level of ambiguity in predicting the values of the input parameters. Coding in the C programming language for UNIX systems was used to create the stochastic simulation weather system and crop development simulation model. A flowchart for the model is shown in Figure.

D. Tactic of Latin hypercube sample selection:

An LHS employs the following methods: Every input parameter's range is split into N intervals, and a single observation is taken on the input parameter in each interval using random selection. Therefore, every one of the K input parameters has N observations (via stratified sampling). Every observation has an equal chance of being picked randomly, thus one observation on X is matched with another observation on X2, and so on until Xk. To determine how sensitive an outcome variable is to the estimated error of the input parameters, one might examine the N observations of each result variable. All of the variables and the input are simultaneously variables in the LHS scheme. The statistical correlations may be evaluated using PRCC since variables are frequently interrelated. A PRCC shows how monotonically an input variable and an output variable are related (Conover, 1980). (Kendall and Stewart, 1979) The PRCC is the relationship between the ith input parameter and the ith output variable.

$$\Upsilon_{X_j,Y} = b_j * ((1 - R^2_{X_j})/(1 - R^2_Y))^{1/2} \quad (17)$$

III. RESULTS

Evaluate if the real and simulated data were in acceptable agreement with regard to significant features like monthly, various agro-climatic seasons, and yearly rainfall. Calculate the likelihood function and the probability distribution of the numerical success. Table I provides a comprehensive comparison of the average monthly rainfall in the Barind Tract. With the exception of the months of April, July, and August, the simulated rainfall is higher than the real yearly, seasonal, and monthly rainfall. Rahman and Alam's conclusion (80The simulated outcome displays an asymptotic normal distribution for the distribution of the success rate. The data was tabulated for the following:

	Simulation	Original
January	2.29	1.52
February	0.88	0.73
March	0	0
April	0.09	0.13
May	5.71	4.97
June	6.34	5.67
July	1.83	2.22
August	2.91	3.64
September	14.08	10.63
October	8.91	8.81
November	0	0
December	0	0
Annual	43.04	38.32
Seasons:		
Rabi	3.17	2.25
%	7	6
Pre-kharif	5.80	5.10
%	13	13
Kharif	34.07	30.97
%	79	81

TABLE I: A correlation of the Barind Tract's average monthly rainfall (Nazipur)

Station parameters			M	O	N	T	H	S				
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Nazipur (Potnitala)												
Po	0.17	0.08	0	0	0.33	0.48	0.23	0.24	0.29	0.28	0	0
P1	0.42	0.33	0.25	0.25	0.58	0.73	0.48	0.49	0.54	0.53	0.25	0.25
P	0.23	0.11	0	0	0.43	0.65	0.30	0.32	0.39	0.37	0	0
Exact mean	7	3	0	0	13	20	9	10	12	11	0	0
Asymptotic mean	7	3	0	0	13	20	9	10	12	11	0	0
Exact variance	9	4.5	0	0	12.3	11.8	10.5	11.3	12.3	11.6	0	0
Asymptotic variance	9	4.5	0	0	12.3	11.8	10.5	11.3	12.3	11.6	0	0

TABLE II Calculate the precise and asymptotic average and variance of the amount of progress, the conditional probabilities (P0, P) for the Markov chain, and the chance of success (P) (suggested by daily simulation rainfall data at Barind)

Estimated values of P	No rain	Rain	Total	Rain/total
0...0.2	201	0	201	0
0.2... 0.4	60	15	75	0.2
0.4...0.6	30	20	50	0.4
0.6...0.8	10	15	25	0.6
0.8... 1.0	2	8	10	0.8
1.0	0	4	4	1

TABLE III shows the correlation between the calculated P values using rainfall simulation results at 5-day intervals and the actual incidence of rain in Nazipur.

Parameters	PRCC
Photosynthetic active radiation	0.95***
Albedo	0.79***
Water stress factor	0.42***
Leaf area index	-0.33***
Temperature stress factor	-0.14**
Plant water evaporation	-0.11*

TABLE IV PRCC calculated from sensitivity analysis

IV. Discussion

The simulation results display the asymptotic normally distributed of the number of successes. For the simulation of monthly rainfall, the following data were tabulated: (1) the predicted conditional possibilities for the Markov chain, (2) the likelihood of progress, and (3) the precise and asymptotic average and variability of the number of rainfall successes. For every month of the Barind Tract, the precise, asymptotic average, and variability of the number of successes are the same (Table II). This is particularly intriguing since, for P values between 0.2 and 0.8, the logistic function is roughly linear in f. (Neter et al., 1989). The class interval was then filled with the estimated P values. Table III, which presents the simulation findings, lists estimated values of P versus no-rain/rain frequency values and the relative frequency of rain. Using the logistic regression approach, you may choose where there is rain or no rain indicated. According to a decision rule put forward by Neter et al. (1989), rain is expected when the projected value of P is more than 0.5 and not when it is less than 0.5. According to Table III, it is nearly impossible for it to rain if the estimated P is less than 0.1. In essence, this kind of data is what provides logistic regression with its advantages over a straightforward threshold method.

The Markov chain maximum likelihood approach and multivariate logistic regression approaches were used to assess the rainfall simulation model (Rahman, 1999b) (Rahman, 1999a). Several comparisons were made between the simulated and actual rainfall data. The findings of these evaluations show that the model's efficiency is typically good.

The PRCC was utilized to determine which factors were most important in the inaccurate result prediction. The size of the PRCC (Table IV) shows how crucial estimation error for the value of the particular variable is in creating the inaccuracy. The PRCC's sign reveals the qualitative connection between the input and output variables. It's crucial to examine the variables' relative importance when ranking them as crucial factors. Four of the seven variables' PRCCs are statistically significant (P 0.001), while the other two are important at the 5

The PRCC data (Table IV) indicate that the estimation errors of the findings of four parameters—photosynthetic active radiation, opacity, water stress component, and leaf area index—are the most significant in determining the forecast imprecision of the above-ground biomass production. Although less important (PRCC 0.33) in terms of their impact on the forecast for the production of above-ground biomass, the uncertainties in the estimates of the values of the last two parameters (Table IV) are statistically significant. The subjective link between the input and result variables is shown by the PRCC's sign. The variables' positive PRCC values imply that the above-ground biomass will increase whenever the input variable's value rises.

V. Conclusion

The leaf area index, thermal stress factor, and crop water evaporation all decline together with the above-ground biomass. Raising the harvest index and increasing sowing density have the potential to boost rice yields in Bangladesh by increasing the leaf area index and capturing more solar energy. By altering the values for crop-specific characteristics in the crop parameter file, this model may be used to simulate various cereal crops like wheat, barley, maize, etc. In order to evaluate various management issues with rice growing that are prevalent in Bangladesh's tropical climate, the model was also updated for that country. The outcomes showed that the rainfall simulation model would function well in various applications.

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