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Projection models for agriculture risk analysis

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Abstract
Due to increasing food demands, high rates of population growth (2-5% per year), and major changes in political, economic and social fragmentation, the agriculture system will be deprived. In the interest of sustainability, we should develop and revise many existing agricultural policies at the national level. Estimation of agriculture risk is the key role for scientists in the revision of crop patterns in different agro climatic zones. In any science, statistics are the fundamental and formidable tool for decision-making theory (projection of agricultural productivity and economic prosperity of the country). More advanced analytical based research will be necessary to make accurate decisions about policy implementation. As of now, there are fewer analytical-based publications cited across the globe. In this pragmatic research gap, statistical methods will play an important role in the development of decision support algorithms by considering the large number of parameters that are collected from the laboratory to the agriculture field. However, decision-makers at all levels need an increasing amount of information to help them understand the possible outcomes of their decisions. For the abovementioned research gap, we attempt to formulate a user-friendly decision-support GIS-based interactive model with greater accuracy to manage the existing agricultural system. The present model will be very useful for agriculture scientists, meteorologists, and policymakers to make the right decisions at the right time for the projection of rainfall with an ambient large substitution of weather parameters, spatial and agricultural management traits. These newer models have eagerly fulfilled all the necessary analytical research interventions for agricultural scientists and policy planners.

Keywords: DSM, GIS, Model, policies, projection, agriculture

Introduction

India is an agriculture-based country. The progress of the country depends on its agriculture system. It is the base of a country's prosperity in terms of economy, infrastructure, poverty, etc. India often faces many problems, *viz.*, lack of food and shelter for poor people, elevated poverty (>45%; hunger index), unemployment, low agriculture productivity, population growth, and periodic hits of infectious diseases (SARS- COV-2, MERS, monkey pox) that are major problems for the economic burden of the country (mitigate the control measures). In addition to that, agriculture has land fragmentation, low rainfall (average rainfall), lack of literacy, migration of farmers to urban settlements, urbanisation, low cost of agricultural products, global warming etc. In light of the above-mentioned problems, our agriculture system is still backward and we have not achieved a good rank in agriculture growth worldwide. One more important problem periodically affecting the farmers is that more than 75-80% of Indian farming depends on rain-fed agriculture. Indian farmers are absolutely and wholeheartedly dependent on rainfall. The current scenario of rainfall is magically acted upon by farming activities. Periodically, rainfall patterns have changed over the past two decades, and also due to a lack of literacy among farmers, Indian farmers have not cultivated agriculture crops according to market requirements. Besides all these reasons, the CASCADE effect on markets, varied cropping patterns in different seasons, lack of forecasting knowledge on weather parameters from scientists using advanced techniques are greatly affecting Indian farming. Currently, the incidence of bankruptcies shows an increased trend. They will take the money from land lords and money lenders at a higher interest rate for their financial needs, such as the purchase of agricultural inputs.

There is no support for a minimum price for agriculture products from the government; dishonesty of the officials for the implementation of various schemes for needy farmers; sublime of the land revenue records in pursuance of taking assured benefits from the government schemes and bank loans for farming, lack of transportation facilities, warehousing and poor performance of the public distribution system etc. Importantly, two decades ago, all state agricultural universities united and rendered services for the farmers welfare, but now, due to political intervention, many universities have not been integrated and are individually spread across the country. Further, in the northern states of India, many farmers depend upon Mahajans for their routine lives, and they will be charged a very high interest rate, so the high cost of borrowing can hinder the growth of the Indian agriculture system. The Indian farmers consider farming a means of subsistence to fulfil the basic needs of their families. Accurate prediction of rainfall is important for farmers in deciding crop patterns and is also considered a game changer. An entire agriculture system will commence with a presumed factor; this underlying assumption should be predicted mathematically and statistically. Today, many NGOs and analytical companies have predicted the rainfall and weather parameters not accurately because of a lack of statistical prejudice. In light of the advancement of forecasting methods, the current research attempts to develop newer forecasting models and diagnostically check the models using real data sets.

Material and Methods

Data sets for model formulation

The primary and secondary data were collected from the selected agro-climatic zones of Karnataka state. Rainfall, weather parameters and GIS spatial data were collected from the Department of Meteorology. The net sowing area, productivity and crop-related virtual data were downloaded from the National Remote Sensing Agency. After data collection, entire data sets are randomly checked in separate software to diagnose the randomness. Data transformation was done using R Studio. Analysis and model demonstration were carried out by R- software. Each individual unobserved component was estimated based on the subgroup analysis, and all the traits of crop management and other associated traits were assigned weighted ranks based on the preceding performance of rainfall and yield. The following mathematical derivation was done for demonstration and to check the robustness of the model.

Model formulation

$$y_{ijk} = \alpha + \beta_j + \gamma_k + (\alpha\beta)_{ij} + \sum_{i=1}^{n} S_{ijk} + \varepsilon^2{}_{ijk} N \sim (\mu, \sigma^2) \quad (1.1)$$

Where, $\boldsymbol{y_{ijk}}$ = Observed value of i^{th} variable j^{th} geographical area with k^{th} plot

α = Effect of i^{th} variable on the mean yield

β_j= Effect of yield on j^{th} area

γ_j = Effect of kth plot (concordance effect of weather parameters)

$(\alpha\beta)_{ij}$ = Interaction effect of ith parameter with j^{th} area

S_{ijk} =Substituion parameters with ith variable j^{th} area k^{th} plot

$\varepsilon^2{}_{ijk}$ = Errors associated with i^{th} variable j^{th} area k^{th} plot

$$\begin{bmatrix} y_{11} \\ y_{12} \\ \cdot \\ y_n \end{bmatrix} = \begin{bmatrix} \alpha_{11} \\ \alpha_{12} \\ \cdot \\ \alpha_{i1} \end{bmatrix} * \begin{pmatrix} \beta_{11} \\ \beta_{12} \\ \cdot \\ \beta_{j1} \end{pmatrix} + \begin{pmatrix} \gamma_{11} \\ \gamma_{12} \\ \cdot \\ \gamma_{k1} \end{pmatrix} + \begin{bmatrix} \alpha\beta_{11} & \alpha\beta_{12} & \alpha\beta_{13} \\ \alpha\beta_{21} & \alpha\beta_{22} & \alpha\beta_{23} \\ \alpha\beta_{31} & \alpha\beta_{32} & \alpha\beta_{33} \end{bmatrix} * \begin{pmatrix} s_{11} \\ s_{12} \\ \cdot \\ s_k \end{pmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{12} \\ \cdot \\ \varepsilon_{ijk} \end{bmatrix} \quad (1.2)$$

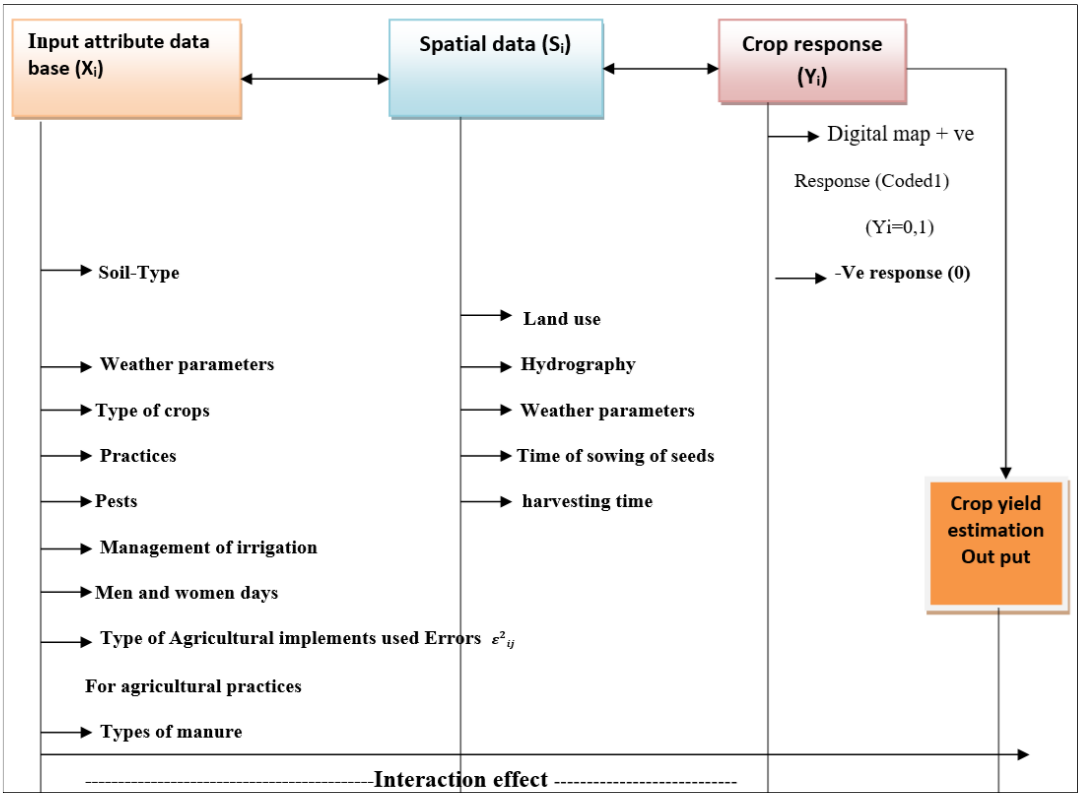

Fig 1: Shows the flow diagram of the model formulation. It describes three components (input crop-attributed data, spatial, and response variables) variables are considered for the model formation.

From the data we categorised different sub groups of exogenous and endogenous variables, the random sample of rainfall $f(x_1, x_2, x_3 \dots . x_n) \epsilon \theta_k; f(X_i) + \varepsilon_t \epsilon \theta_k$; and other traits $f(y_{1i}, x_{2i}, x_{3i} \dots . x_{ni}) + \epsilon \theta_k; f(y_{ij}) + \varepsilon_{tj} \epsilon \theta_{jk}$.All data series is normally distributed $X_i \sim N(\mu, {\sigma_i}^2)$ and $Y_{ij} \sim N(\mu, {\sigma_{ij}}^2)$

$$\begin{bmatrix} y_{11} \\ y_{12} \\ \cdot \\ y_n \end{bmatrix} = \begin{bmatrix} \alpha_{11} \\ \alpha_{12} \\ \cdot \\ \alpha_{i1} \end{bmatrix} * \begin{pmatrix} \beta_{11} \\ \beta_{12} \\ \cdot \\ \beta_{j1} \end{pmatrix} + \begin{pmatrix} \gamma_{11} \\ \gamma_{12} \\ \cdot \\ \gamma_{k1} \end{pmatrix} + \begin{bmatrix} \alpha\beta_{11} & \alpha\beta_{12} & \alpha\beta_{13} \\ \alpha\beta_{21} & \alpha\beta_{22} & \alpha\beta_{23} \\ \alpha\beta_{31} & \alpha\beta_{32} & \alpha\beta_{33} \end{bmatrix} * \begin{pmatrix} s_{11} \\ s_{12} \\ \cdot \\ s_k \end{pmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{12} \\ \cdot \\ \varepsilon_{ijk} \end{bmatrix} \quad (1.2)$$

$$\hat{y} = (\alpha'\beta')^p \gamma + \begin{bmatrix} \alpha\beta_{11} & \alpha\beta_{12} & \alpha\beta_{13} \\ \alpha\beta_{21} & \alpha\beta_{22} & \alpha\beta_{23} \\ \alpha\beta_{31} & \alpha\beta_{32} & \alpha\beta_{33} \end{bmatrix}^{-1} * \begin{pmatrix} s_{11} \\ s_{12} \\ \cdot \\ s_k \end{pmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{12} \\ \cdot \\ \varepsilon_{ijk} \end{bmatrix} \quad (1.3)$$

Where $\alpha'\beta' =$ Cross multiplication matrix, p = number of parameters,$\gamma =$ number of farming plots. Asper the eqn (1.3) we attempted to reduce the randomness on each variable, the above eqn was generalized and linearly modelled by the following equation.

$$Y_n = \left(\frac{1}{1+exp^{(\alpha\beta)^n}}\right)^{1/p} s_k \quad (1.4)$$

Y_n = n^th dependent variable,$(\alpha\beta) =$ intercept and slope of regression coefficients
$s_k =$ Substitution parameters

In case of agriculture, the estimation of likelihoods on exogenous and endogenous variable is very difficult because due to periodicity of rainfall (periodic changes), drastic changes in global warming from greenhouse effect , deforestation for urbanisation , mining in forest areas, increasing trend of particulate matter (PM_{10} &$PM_{2.5}$), fragmentation of agriculture land, cultivation on the infertile or barren land, lack of labour force , financial inconsistency for purchasing of agricultural inputs (chemical fertilisers, seeds and farm yard manure), sudden outbreak of plant diseases and insects , there is no mechanised equipments for post harvesting, lack of improved agricultural implements, price fluctuation of farm implements and inputs, lack of knowledge on agricultural marketing facilities and CASCADE effect price variation of perishable crops , there is no proper storage facilities, lack of transportation , selling of agriculture produces for middleman, lack of financial supports from government and NGOs, bankruptency for agriculture crops, lack of crop insurance , cultivation of land on traditional basis , culture and beliefs on agriculture is the strongest manifesto for the accurate estimation of likelihood in agriculture system. In those particular instances, agriculture scientists and statisticians have attempted to formulate various cropping patterns in different agro climatic zones. The substitution factor is a unique domain to derive the mathematical situation in the above-mentioned thrust area of agriculture. The equation (1.4) deals with the estimation of likelihoods for a single substitution variable. Suppose we extend our scope to substitute a larger number of variables; the above equation becomes

$$\boldsymbol{y_{ijk}} = \left(\frac{1}{1+exp^{(\alpha+\beta_0 X_0+\beta_1 X_1+\beta_2 X_2 \dots\dots \beta_n X_k)^{1/2}}}\right)^{1/p} S_{ijk} + \varepsilon_{ijk},$$
$$\varepsilon_{ijk} \sim \mathrm{N}(0, \sigma^2) \quad (1.5)$$

Likelihood estimation of individual variables, the eqn (1.5) becomes

$$\mathrm{Log}\left(\frac{\mathrm{P}}{1-\mathrm{P}}\right)^{1/\mathrm{p}} \mathrm{S_{ijk}} + \varepsilon_{\mathrm{ijk}} \quad (1.6)$$

Where Upper case P= probability value, lower case p = number of parameters
From the equation(1.5) we explored the trend of each individual variables , it was modelled by the following equations

$$\boldsymbol{y_{ijk}} = \alpha x + \beta, \alpha \neq 0 \text{ Linear} \quad (1.7)$$

$$\boldsymbol{y_{ijk}} = \alpha_0 x^2 + \beta_0 + c, \alpha \neq 0 \text{ Quadratic} \quad (1.8)$$

$$\boldsymbol{y_{ijk}} = \alpha_0 {X_0}^2 + \beta_0 {X_0}^2 + \alpha_1 {X_1}^2 + \beta_1 {X_1}^2 + .. \alpha_2 {X_2}^2 + \beta_2 {X_2}^2 + \cdots \alpha_n {X_k}^2 + \beta_n {X_k}^2 + {\varepsilon^2}_{ijk}, \alpha \neq 0 \text{ Polynomial}$$
(1.9)

If the variable components is unobservable , the distribution of random variable shows exponential distribution , trend of the variables were measured by exponentially

$$y = \alpha e^{\beta X_i} \quad (1.10)$$

$'\beta' is the$Relative rate $\beta = \frac{\sum(l_n Y - avg(l_n y) * (x-\bar{x})}{\sum(x-\bar{x})^2}$, $e = 2.718$ X_i = the random variable observed components.

Model forecasted

The above formulated model was transformed into the forecasting approach in the following techniques. By using this following model we have predicted forecasted values at defined time intervals of ' (t+i)'

$$\mathrm{P(t+i)} = G(t) + \mathrm{i}*(\mathrm{T(t)}*\mathrm{s(t-L+i)}) \quad (1.11)$$

$$A(t) = A(t-1) + T(t-1) + \alpha\left[\frac{V(t)}{S(t-L)} - G(t-1) - T(t-1)\right] \quad (1.12)$$

Where,$A(t)$ =Different agro climatic zone at time 't' (t = 0,1,2,3...n^th year), i= width of the time
$T = trend, \alpha =$ Parameter value, $V(t)$= Selected time period (t=3,6,12,24 months) ; $S(t-L) =$ Seasonal component at time ' t' with (t- L) l= Lag period. The trend value was smoothened by the following eqn (1.13)

$$T(t) = T(t-1) + \beta[(t) - G(t-1) + T(t-1)] \quad (1.13)$$

$$S(t) = S(t-L) + \gamma\left[\frac{V(t)}{G(t)} - S(t-L)\right] \quad (1.14)$$

For constant model, the parameters are $T(t) = 0\beta = 0S(t) = 1.0\gamma = 0$.In case of trend and seasonal effect, the parameters were

$$S(t) = 1.0\gamma = 0 \,; T(t) = 0\beta = 0$$

Agriculture risk analysis latent effect partial Markova chain model (ARPMCM)

Model Assumptions

The present agriculture system will be dependent on the posterior events (projection of previous rainfall, weather parameters like temperature, RH, wind movement, cloud, etc.). These probable parameters will make the process memory-less as it is solely dependent on the current state and the randomness of the transition for the next state of the events. In this model, we formulated three state parameters: (i) states: all the states of weather parameters can fall within the state spaces of the dynamic system; (ii) the initial state distribution: an initial state parameter probability distribution of the starting state. This was encoded into a column vector denoted as "q." (iii) State transition probabilities: the transition probability has moved from one state to another as encoded. $S = \{S_0, S_1, S_2 \ldots . S_t\}$ with space $q = \{q_0, q_1, q_2 \ldots . q_t\}$on the inititial probability distribution 'q'

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{1S} \\ P_{21} & P_{22} & P_{2S} \\ P_{31} & P_{32} & P_{3S} \end{bmatrix}_{S*S}$$ => Transition probability state matrix (1.15)

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{1S} \\ P_{21} & P_{22} & P_{2S} \\ P_{31} & P_{32} & P_{3S} \end{bmatrix}_{S*S} = \sum_{j=1}^{S} P_{ij} =$$

1 , each row is equal to 1 (1.16)

$$P_{ij} = P(X_{t+1} = j, X_i = i), \forall_{i,j}\, \epsilon\, S \ \leq t = 0,1,2..\text{n} \quad (1.17)$$

A Markova process associated with a sequence of possible events on agriculture risk from land ploughing to end (storing of food grains), in which the probability of each event depends on the probable transition state variable attained in the prior events. Countable infinisible events were moved to states with discrete time space (the discrete time Markova chain). Further, the Markova random walk was started in the study phase, and our system events (Ni= number of vents) will cause overlapping situations to draw the agriculture decision at the right time. The sample steady state space will be converged to the transition probability of 'P," and again, the model will be a converged semi-Markova decision process.$S_1 \to S_2 \to S_2 \to S_3 \ldots . \to S_n$Where$S_1$ to S_n state of system.

The transition probability $P(S_n \to S_{n+1})$ moved with stochastic matrix in eqn(1.2)

$$P(S \to S') \geq 0 \ \sum P(S \to S') = 1 \quad (1.18)$$

In the above eqn (1.72), the distribution of S_{n+1} depends only on S_n (n^{th} sequencing by real definition of Markova chain)

We consider the frequency of events repeated at n^{th} time , the eqn will be $f_n(S)$, it can be evolved according the different stages of insertion and deletion of many events

$$f_{n+1}(S') = \sum_s f_n(S) P\ (S \to S') \text{Or } f_{n+1} = P f_n \quad (1.19)$$

If the individual event are having Eigen function $= p\emptyset = \varepsilon\emptyset$, where 'p' is the positive , the negative value $\varepsilon \leq 1$; equilibrium state $\varepsilon = 1$.

The sequential event $S_n \to S_{n+1}$has converges ergotic distribution, the converges of multiple events are geometrical and monotonic

$f_n(S) = \pi(s) + \sum \lambda^n C_\lambda \phi_\lambda\ (s)$if $\varepsilon < 1$ after 'n' iteration then becomes zero (1.20)

By using transition rules we consider two state S_m and S_n has linked by the transition probabilities $P(m \to n)$, suppose we are determined the reliability of each individual consensus of events (success or failure) with multiple arrays , then it has a (60%) chance of event on the first and followed by next event so on. The percentage variation changes will be observed on the subsequent events.

Success of agriculture system without substitution of parameters

$$P(S \to S') = \begin{bmatrix} 0.60 & 0.40 \\ 0.30 & 0.40 \end{bmatrix}$$ Loop /with out

Suppose, the events will be initially equally likely to be yield response is positive or negative

$$\pi(1) = [0.50, 0.50\ ]$$

The probability of event on the next read of homology will be

$$\pi(2) = T\ (1 \to 2)\pi\ (1) = \begin{bmatrix} 0.60 & 0.40 \\ 0.30 & 0.70 \end{bmatrix} (0.50,0.50\ ) = (0.45\ , 0.50)$$

$$\pi(2) = T\ (2 \to 3)\pi\ (1 \to 2)\ \pi\ (1)\ \pi\ (2) = (0.43\ , 0.56)$$

$$\pi = \log_{Lim\ x \to \infty} T^x \pi = \left(\frac{3}{7}, \frac{4}{7}\right) = (0.42,0.57)$$

$\pi = T\,\pi$Asa Eigenvalue problem

The detailed events were described by $\pi(s)P(S \to S') = \pi\ (S')P(S' \to S)$

$$\sum_s \pi(s) P(S \to S') = \pi\ (S') \sum_s P(S' \to S) = \pi(S') \quad (1.21)$$

Events are possible to stay in the same steady state, the model becomes

$$P(S \to S) = 1 - \sum_{S' \neq S} P(S' \to S) \quad (1.22)$$

$$P(S' \to S) = T\ P(S' \to S) \left[\frac{\pi\ (S')}{\pi(S)}\right] S \neq S' \quad (1.23)$$

Discrete time stochastic Process

The state of the system was observed at discrete instant at time 't'. A group of events are sequenced at different time interval and form a Markova chain model.

$$P(X_{t+1} = S / X_t = S_t, X_{t-1} = S_{t-1} \ldots . . X_1 = S_1, X_0 = S_0) \quad (1.24)$$

X_{t+1}= Sequencing of events at 't+1 ' t=0,1,2..n with different consonance $S_0, S_1, S_2 \ldots S_t$ S is the Discrete Markova containing random variables transitioning from one state to another depends on certain assumptions and definite probabilistic rules having the Markova property.

Model diagnostic test

Many diagnostic tests were used for robustness of the model, the present model was diagnostically tested by Akaike information Criterion (AIC).

$$AIC = -2\ lnL\{M_i/Y\} + 2p_i \quad (1.25)$$

Where, $lnL\{M_i/Y\}$is the negative likelihood, $p_i =$ is the number of model parameter

Y=is the observed data, M_i= hypothesis (model)

Results and Discussion

Numerical simulation of the model

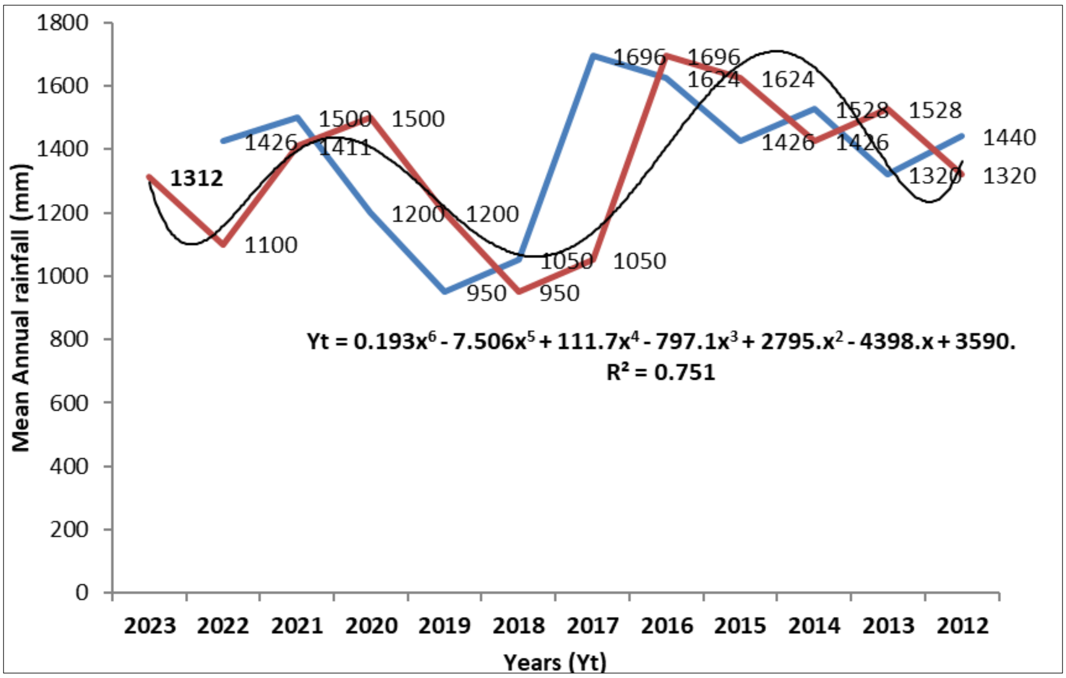

Fig 1: Trend of rainfall (mm) in Karnataka State over one decade (2012-2022)

Table 1: Simulation of mean annual rainfall (mm) based on weather parameter substitution method

Time	Naïve ($\beta = 0.38, \alpha = 0.01$)				Exponential Smoothing ($\beta = 0.38, \alpha = 0.01$)			$(t-\bar{t})$	Regression $(t-\bar{t})*(y_t-\hat{y})$	$(t-\bar{t})^2$
	Y_t	F_t	ε_t	$\varepsilon_t(\%)$	F_t	e_t	$\varepsilon_t(\%)$			
2021	1500	-			-			-4.5	-696.3	30.25
2020	1200	1500	-300	25	1500	-300	25	-3.5	780.3	20.25
2019	950	1200	-250	26.32	1386	-436	45.89	-2.5	1481.9	12.25
2018	1050	950	100	9.52	1220.32	-170.32	16.22	-1.5	808.5	6.25
2017	1696	1050	646	38.09	1155.6	540.4	31.86	-0.5	-483.9	2.25
2016	1624	1696	-72	4.43	1360.95	263.05	16.20	0.5	-125.3	0.25
2015	1426	1624	-198	13.88	1460.91	-34.691	2.45	1.5	26.3	0.25
2014	1528	1426	102	6.68	1447.64	80.36	5.26	2.5	231.9	2.25
2013	1320	1528	-208	15.76	1478.18	-158.18	11.98	3.5	-133.5	6.25
2012	1440	1320	120	8.33	1418.07	21.93	1.52	4.5	233.1	12.25
$\sum e_t$				148.01			81.46			92.50
2022	$\hat{y}_t$ 1426					$\hat{y}_t$ 1699				$\hat{y}_t$ 1247
2023	1258					1236				1318
MAE					117.47			120.85		
MSE	221.78				26203			26258		
MAPE	76919.11				9.05%			11.28%		
Akaike	16.45%				3642			2855		
Likelihood ratio	125.22				136.05			132.19		
R^2(%)	0.82				0.93			0.86		

The three models (naive, exponential smoothing, and regression) were demonstrated with varying parameters (temperature, relative humidity, wind movement, ocean current, etc). As per the model results, the smaller errors were seen in exponential smoothing (ε_t= 81.46%), followed by regression (ε_t= 92.50). The maximum errors were associated with the naive model (14.80%). The maximum rain fall was forecast by Thompson iteration techniques with a lag of 3 years. The least average rainfall was seen in 2019, and the maximum was found to be in 2017. The highest likelihood ratio was seen in exponential smoothing (136.05) as compared with regression (MLEs =132.019) and the naive model (MLEs = 148.01). The succeeding year's maximum rainfall was predicted in regression (1318 mm), followed by naive (1258 mm) and exponential smoothing (1236 mm) Table 1. The akike and all statistical parameters were found to have significant values for formulating and predicting massive data sets in larger geographical areas. Due to the difficulty of estimating random variation among exogenous and endogenous variables in present agriculture, because cropping patterns and weather parameters are fragile, each variable is highly connected with some degree of probability and presumption (e.g., lower interface between farmers and agriculture system). Assuming the rainfall and yield based on the posterior information, the degree of uncertainty will vary in different agro-climatic zones and geographical areas. If one agro climatic zone received a very good RF and another fetched a deficit RF due to varying climatic conditions and weather parameters, For this practical reason, we superimposed all the parameters and assigned weighted ranks for the construction of a newer model, ' Semi-Markova latent effect PCA model'. By using this model, we explored latent effects and probable likelihoods in different years on a sequential basis. All the parameters were assembled and formulated on the basis of a weighted scale for different rainfall sequences.

Table 2: Markova chain Latent Probability of RF vector with different sequences

Year	Events	S_1	S_2	Formula
2012	S_0	1	0	Initial State
2013	S_1	0.7	0.3	$S_0 \times P = S_0 \times P^1$
2014	S_2	0.55	0.45	$S_1 \times P = S_0 \times P^2$
2015	S_3	0.475	0.525	$S_2 \times P = S_0 \times P^3$
2016	S_4	0.437	0.562	$S_3 \times P = S_0 \times P^4$
2017	S_5	0.419	0.581	$S_4 \times P = S_0 \times P^5$
2018	S_6	0.409	0.591	$S_5 \times P = S_0 \times P^6$
2019	S_7	0.405	0.595	$S_6 \times P = S_0 \times P^7$
2020	S_8	0.402	0.598	$S_7 \times P = S_0 \times P^8$
2021	S_9	0.401	0.599	$S_8 \times P = S_0 \times P^9$
2022	S_{10}	0.401	0.599	$S_9 \times P = S_0 \times P^{10}$
R^2(%)		0.89		

Note: S_1&S_2 State variables of RF on observed and predicted

In the models output presented in Tables 1 and 2, the initial event year 2012 RF has been considered a state variable. On a sequential basis, we determined the latent effect of rainfall from observed data series, an initial case S_1 and S_2, and the probability value was presumed 1 and 0 (1 coded received more than average rainfall over ten years and 0 coded less than average RF). Subsequently, the model was demonstrated by different iterations of the Bootstrap method Table 2. As per the output of the formulated model, all sequential years iterated the latent probability with marginal ranges between 0.40 and 0.7. In the year, the latent effect was significantly correlated (p = 0.70) with the coefficient of determination (R^2 = 0.89) Figure 3.

Table 3: Semi Markova latent effect calculated based on PCA

Year	PC_1	PC_2	Eigen value PC_1 PC_2	%Variance PC_1PC_2
2012	0.047	0.15	1.38 0.61	69.31 30.68
2013	1.26	0.28	1.22 0.88	73.00 27.00
2014	0.40	-0.31	1.41 0.34	65.22 34.78
2015	-0.28	0.88	<1.0 1.44	64.00 36.00
2016	-1.97	0.76	1.65 1.25	74.85 25.12
2017	-2.41	-0.30	<1.0 0.98	76.32 23.68
2018	-0.080	-2.03	<1.0 1.01	63.22 36.78
2019	1.64	0.14	1.33 0.65	58.95 41.25
2020	0.80	0.55	<1.0 1.22	63.47 36.53
2021	0.52	-0.36	<1.0 1.41	68.54 31.46
2022	0.17	0.59	<1.0 1.87	69.96 27.00
2023	-0.11	-0.36	<1.0 1.66	78.89 21.11

Steady state S_1=0.4 ,S_2=0.60

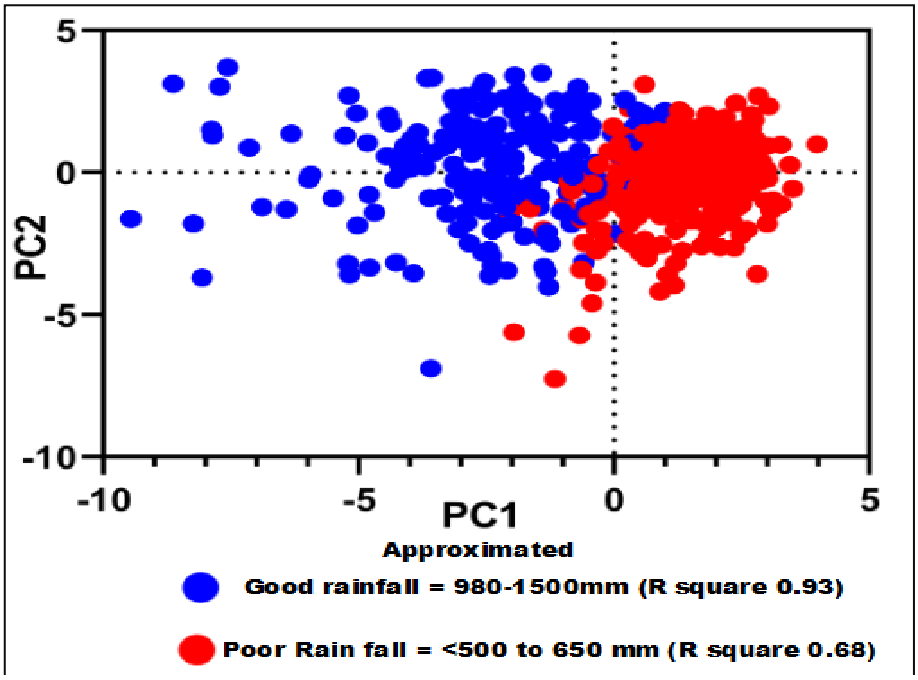

Fig 2: Semimarkova PCA Plot on the mean rainfall in 2023

The parameters were rotated by PCA analysis, and most of the years in PC2 had very good Eigen values (69.32%) (Figure 2). Only 2012, 2013, and 2017 had less than one Eigen value because of randomness in the data sets. The periodicity of the rainfall varied in selected regions of Karnataka.

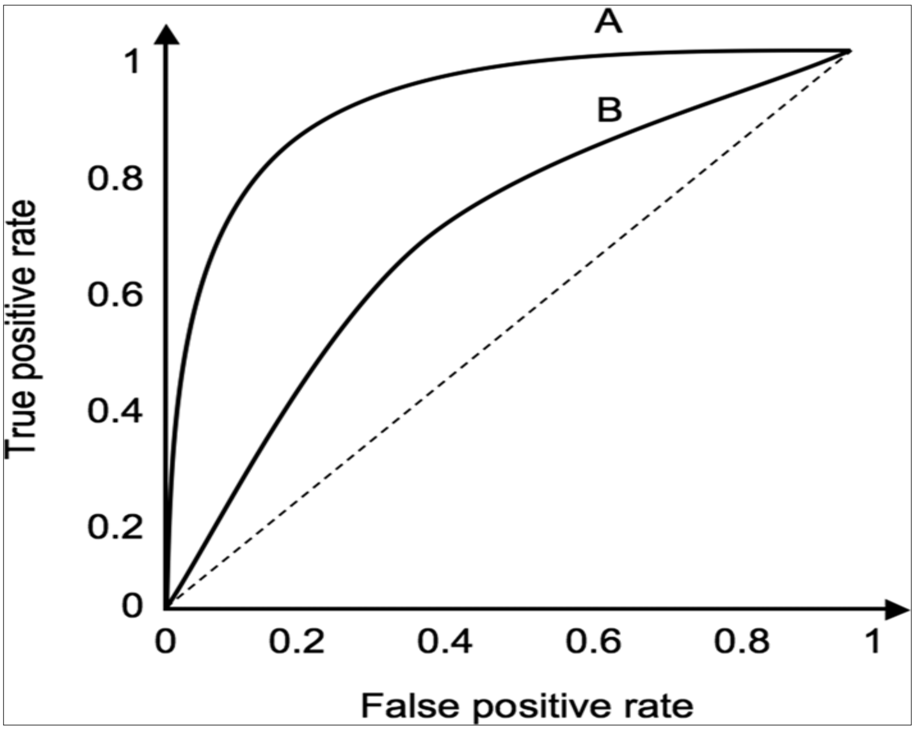

Fig 3: Yield response substituted all weather parameters (A- Good response; B-moderate response

Discussion

Rainfall is a unique parameter for optimising the crop yield. We optimise the use of limited traits for maximising and sustaining the productivity of yield based on the weather parameters. Geographical information is one of the most successful integrated areas to explore the advanced prediction of forecasted agriculture parameters discussed by [1, 3]. At the worldwide fitted water quality models AGNP (agriculture non-point source) and ANSWERS (real non-point source watershed environmental response simulation), both models supported the runoff and water quality measures in dry land agriculture. The present formulated model can easily forecast the rainfall by using various substituted parameters with a more significant value of iteration and a lesser standard error (9.05%). These aspects of the model were discussed by the [4, 5]. Other well-known models EPIC developed by [6]. The sequences of time St (state dynamic substitution) had more iterations required for running the model, as they were greatly affected by the substitution factors and required > 100 time iterations for rendering model inputs were discussed [7]. By using this model, we will be able to visualise the 3D dimension forecasting figure at the national level, as it is necessary to update the model on a customised basis [8, 9, 10]. We can even use this formulation for extending machine learning models for forecasting the risk of theory of economy, collision analysis of orbits in astronomy, estimation of breeding values considering all traits, farmer feedback analysis, study population dynamics, disease dynamics, biochemical assays, transcriptomics, proteomics, etc. The integration of the GIS substitution Markova model will yield very good results with a quotient of errors that have been eliminated without any iteration, particularly for massive data series with time intervals. A similar model was proposed by [11, 12] which formulated AGNP to display and facilitate formidable output. Similar studies were extended in the form of new models, ANSWERS and Grass GIS [13, 14]. This model has accomplished smaller iterations with excellent inputs, and rendering of results can take lesser time intervals (1-3 minutes). Both AGNP and ANSWERS are single-event distributed parametric models that require a watershed to be divided into square grids and resampled like raster-based GIS, where the data sets are sorted in a grid-like array. Our formulated model and data series have not been sorted; raw data can be imported for analysis purposes in the form of numerical arrays. There is no limitation on the data series; within a fraction of a minute, the data series would be executed, and the process of output would be generated with the highest accuracy and precision of the data reproducibility [14]. There are most significant merits that are noticed in the present model *viz* good reproducibility, lower rendering time and better scope. We substituted and imported the data on the basis of the logical basis of a single vent with multiple components and a continuous distribution of data series with defined time intervals [15, 16]. These methods of synchronising inputs were carefully examined within the model itself before rendering the outcome. In case we can estimate the yield response from this model, the entire area should be integrated based on weather forecast parameters, and each agro-climatic zone should be subdivided to manage the homogeneity (the collection of inputs for such models is often difficult due to the level of aggregation and the nature of spatial distribution). This process will need more time, to overcome this problem shown and discussed in reference [17, 18, 19] developed a GIS interface to automate inputs to a continuous time, distributed parameter model called the Soil and Water Assessment Tool (SWAT). A digital elevation model (DEM) created in GIS is an important input to this model [19, 20]. Given an input surface such as DEM, the hydraulic modelling tools can be used to generate grids that encode the flow direction and accumulation for each cell or grid, representing logical and natural climatic conditions and the topology of the agriculture system. The [20] used GIS and ILWIS (integrated land and water information system) to predict average soil loss through the USLE (Universal soil equation) model. This model will allow us to study the extent and rate of change now occurring in the development of information agriculture analytical technologies, which have opened the way for significant changes in crop production at selected sites and the management of agricultural decision making. This vision has been reflected in precision farming. The precision or site specific farming aims would be correlated with the transient probabilities of all unknown parameters and also directed to draw the decision on the application of seeds, fertilisers, pesticides, and water holding capacities in black and sandy loamy soils in farmer's fields. Our forecasted model will clearly envisage how to optimise farm returns and minimise chemical inputs, environmental hazards likelihoods estimated. Markova chain modelling is able to demonstrate that farming systems utilise some combination of GPS receivers, continuous yield sensors, remote sensing, egotistic, and variable rate treatment applicators with GIS. GPS (Global Positioning System) is one of the many new technologies contributing to precision farming, and is the one that really puts the precision into farming for most site-specific operations in terms of input use, while reducing or avoiding long-term environmental degradation. Adoption of this technology requires accurate geographical maps showing physical and chemical properties and the tools to apply the inputs as per the spatial variability. The concepts embodied in precision agriculture offer the promise of increasing productivity while decreasing production costs and minimising environmental impacts. Precision agriculture is considered a suite of technologies consisting of crops, weather, pest complexes, and marketing arrangements rather than a single technology. All these components have the common feature of increasing the information intensity of agriculture. Precision farming and agriculture require new approaches to research that are explicitly designed to improve understanding of the complex interactions between multiple factors affecting crop growth and farm decision making. Understanding the complex interactions among the multiple factors affecting crop growth is the foundation of any attempt to improve management systems. Precision agriculture is changing the way in which agricultural research can be accomplished.

Conclusion

Today's agriculture is fragile; each event can encompass many risk factors, from seed sowing to harvesting. In India, many factors are hindering good practises, including infringement of political freebies, , lack of proper agricultural inputs, and a lack of marketing facilities. A farmer is presumed to correlate good rainfall with yield every year. Unfortunately, it seems to be true due to drastic climatic conditions and global warming. In the twenty-first century, agricultural professionals will use information technologies to play an increasingly important role in crop production and natural resource management. Increased use of fertilisers, pesticides, and other chemicals has contributed to the enhancement of agriculture's productivity in recent decades. But currently, agriculture production is facing many challenges, such as increased costs of production, shortages of irrigation water, adverse impacts of agriculture on the environment, etc. For countries like India, it will be a challenging task to meet the food demands of the growing population in the future. Further, to survive in the highly competitive world market for agricultural commodities in view of globalisation, agricultural producers must produce highly quality products at low prices while using environmentally sound practises. In this context, GIS has a significant role to play in the decision making process in agriculture at various levels, i.e., field, regional, national, and global levels. A GIS statistical model is one of the important tools of information technology (IT) that is highly relevant to agriculture. This technology allows examining and handling a wider range of spatial data bases, such as soils, hydrology, weather, etc., and integrating them with socio economic variables. Simultaneous examination of these variables leads to a better understanding of various agriculturally related processes and their interactions over space and time. This leads to accurate characterization of resources and identification of appropriate domains to target new technologies. The current model is more robust to forecast all parameters accurately and technically advise the specialists to take the right decision at the right time.

Future Scope

i) In terms of simulation, the generation of massive amounts of data on the farm will enable dynamic experimentation that could supersede the use of traditional experimental plots. The agricultural system may need to evolve so that innovation and learning can exploit both traditional research plot experiments and information captured from actual field operations. Incorporating information about variability in soils, moisture, nutrients, and pest populations into decision-making requires an understanding of crop growth in an environmental context, which is more complex for model formulation.

ii) Traditional plant and soil science research has not been designed to forecast future action. In this current paradigm, we are unable to control various error factors in experiments, in which one or more factors are varied while others are held constant. For that particular reason, the model was not suited.

iii) In agriculture, experimental design can correspond poorly to a real farm context, in which multiple factors vary simultaneously. Such experiments provide little information about how responses to variations in any one factor change as other conditions change. New information technologies will be required to make the more detailed and timely decisions necessary for precision agriculture.

iv) The collection of data series is unprecedented because of ridiculous changes in climatic conditions, soil, crop, pest, and weather observations. Maps created using GIS software can be used during field operations to make more precise and timely applications of inputs. Multidisciplinary research will be needed to match measurement methods and analytical techniques with crop production questions of interest to effectively understand and use information about the true variability of measurable parameters within farm fields. Database management and image processing methods are needed to extract useful information from very large data sets. Geo-statistical methods must be advanced both to more effectively sample and to more accurately interpolate sparse data. Spatial analysis methods and spatially explicit components in crop models should be evaluated, calibrated under field conditions, and linked to GIS to facilitate accurate analysis and inference from collected precision agricultural data.

v) This model was demonstrated only in a limited area with massive data. More research work will be needed to check the reproducibility and achieve greater accuracy.

Though the Akaike information criterion (AIC) is used for the robustness of the model for the given data sets, we provided likelihood ratios (LRs) for a common man to understand and comprehend the results. The analysis is based on the data sets available for Karnataka State in India. The above models can also be used for other states of India, depending on the type of data sets and the prevailing weather and environmental conditions. If necessary, the above models have to be modified to carry out the analysis. A summary measure can be obtained for India by pooling each state measure with appropriate weights. The present models will pave the way for a better understanding of the agricultural system in India.

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Conflict of interest
There is no conflict of interest between any funding agency and line Government line Departments

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