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COMPARATIVE EVALUATION OF POTATO CULTIVATION AND STORAGE CONSTRAINTS FOR POTATO PRODUCTION IN WEST BENGAL

Jamuna Prasad Kundu[1], Manik Chandra Das[2]*, Bivash Mallick[2] and Bijan Sarkar[3]

ABSTRACT: Potato is the second most important and widely cultivated crop after cereals in West Bengal. The state's high potato production is primarily attributed to the favourable climatic conditions in the districts of Hooghly, Paschim Medinipur, Purba Bardhaman, and Bankura. However, farmers in these four districts face numerous challenges related to potato cultivation and storage, which adversely affect both yield and the edible quality of potatoes. Through focus group discussions and interviews with key stakeholders, fifteen major constraints in potato cultivation and storage were identified. Data on these fifteen constraints were collected based on four response variables *severity*, *occurrence*, *detection*, and *environmental impact* via a survey conducted in sixteen major potato-growing blocks across these four districts during the year 2025. The relative weights of the four response variables were determined using the Fuzzy-AHP (Fuzzy Analytic Hierarchy Process) method, and the fifteen constraints were ranked using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach with statistical analysis of the survey data. The TOPSIS analysis revealed considerable variation in the relative criticality of the identified constraints affecting potato cultivation and storage. Among the 15 constraints evaluated, Constraint 1: "access to quality seeds at an affordable price," obtained the lowest TOPSIS score of 0.3320, indicating that it was the most critical constraint in the study area. In contrast, Constraint 14: "pest attack during storage," recorded the highest TOPSIS score of 0.8214, and was consequently ranked as the least critical or most favourable constraint among the 15 constraints. Thus, the findings can assist policymakers, agricultural extension agencies, seed suppliers, cold-storage operators, and other stakeholders in developing targeted and priority-based interventions rather than adopting a uniform approach to all identified constraints.

KEYWORDS: Potato; Cultivation; Constraints; Fuzzy- AHP; TOPSIS.

INTRODUCTION

The potato (*Solanum tuberosum* L.) is a worldwide essential and important staple crop, widely produced and consumed due to its affordability, large scale production and easy accessibility in free markets. It offers essential nutrients including carbohydrates, dietary fiber (mainly in the skin) and various vitamins and minerals such as magnesium, potassium, and iron (Campos and Ortiz 2020; Devaux *et al*., 2021; Raigond *et al*., 2020).

West Bengal with unique geographical position, varied soil classification and different climatic condition, produce a wide variety of cereals, oil seed, fruits and vegetables is the second largest potato producer state

*Corresponding author; email: manikchandra.das@makautwb.ac.in
[1]Department of Mechanical Engineering, Mallabhum Institute of Technology, Bishnupur, Bankura, West Bengal, India.
[2]Department of Industrial Engineering and Management, Maulana Abul Kalam Azad University of Technology, West Bengal, India.
[3]Department of Production Engineering, Jadavpur University, Kolkata, West Bengal, India.

in India after Uttar Pradesh (Bhattacharyya and Mitra 2014; Islam et al., 2024). Potato is particularly important for farmers in districts such as Hooghly, Paschim Medinipur, Purba Bardhaman, and Bankura in West Bengal, where a considerable area is devoted to potato cultivation. Potato is affected similar to other crop by a lot of abiotic and biotic stresses (Kroschel *et al*., 2020 and Singh *et al*., 2021). These abiotic and biotic stresses are serious potato cultivation constraints in potato producing field (Okonya *et al*., 2014). They are ranged from the attach of insect developing blemishes and therefore the tuber quality and yield are significantly reduced (Demirel 2023; Demirel *et al*., 2020; Misganaw 2016; Sahu *et al*., 2023) The effective potato crop protection management strategies would be implemented during growth, harvesting, post harvesting and storage by removing these stresses to improve the potato productivity in West Bengal (Kitinoja 2013 and Sen *et al*., 2018). A cold chain arrangement is required because of perishable nature of potato (Aung and Chang 2014; Pinhero *et al*., 2009) It helps to maintain the quality and extend the shelf – life, if consumption is not meant immediately after harvest (Alamar *et al*., 2017). In the absence of sufficient cold storages and related cold chain facilities, the farmers of West Bengal are being forced to sell their product immediately after harvest which results in glut situation and low-price realization. A cold storage facility accessible to them will go a long way in removing the risk of distress sale and ensure better returns (Datta *et al*., 2015). Beyond its critical contribution to global food security, the potato possesses distinct genetic characteristics and a deep cultural heritage, rendering the crop highly valuable for both agricultural production and genetic studies (Mangal *et al*., 2024).

Despite of high production potential, potato cultivation and post-harvest management in West Bengal are affected by several interconnected technical, climatic, economic, infrastructural, and institutional constraints. Although individual constraints have been discussed extensively in agricultural research, identifying the relative criticality of multiple constraints simultaneously remains a challenging decision-making problem. Different constraints may vary considerably in terms of their severity, frequency of occurrence, detectability, and environmental consequences. Moreover, the assessment of agricultural constraints generally involves expert judgments and farmers' perceptions, which are inherently subjective and uncertain. Conventional ranking approaches based only on individual indicators may therefore fail to adequately represent the complexity and uncertainty associated with potato production and storage constraints. A systematic prioritization framework is consequently required to identify the most critical constraints and provide a rational basis for intervention and resource allocation. To address this gap, the present study employs an integrated Fuzzy-AHP and TOPSIS framework for systematic prioritization of potato cultivation and storage constraints in West Bengal. Fuzzy-AHP is particularly suitable for determining the relative importance of evaluation criteria because it can incorporate the vagueness and uncertainty inherent in human judgments. Instead of requiring experts to provide precise numerical assessments, fuzzy numbers can represent linguistic evaluations and thereby provide a more realistic representation of expert knowledge. The method is therefore appropriate for assigning criterion weights when the assessment of agricultural constraints involves subjective perceptions and incomplete information.

The study has been undertaken to (i) identify the major constraints affecting potato

cultivation and storage in West Bengal, (ii) evaluate the identified constraints based on severity, occurrence, detection, and environmental impact and (iii) prioritize and rank the constraints to identify the most critical factors requiring management intervention.

Through focus group discussions with relevant stakeholders, fifteen key constraints related to potato cultivation and storage were identified. These constraints were analysed using multivariate statistical tools such as mean vector analysis, correlation matrix, and hypothesis testing. Finally, the constraints were ranked using the Fuzzy-AHP and TOPSIS method.

MATERIALS AND METHODS

Survey area

The survey was conducted in four major potato-producing districts of West Bengal, India, located between 85°50′ and 89°50′ east longitude and 21°25′ to 27°13′ north latitude. The study area comprised 16 potato-growing blocks within the districts of Hooghly, Paschim Medinipur, Purba Bardhhaman and Bankura. These blocks are Tarakeswar, Singur, Khanakul, Pursura, Chandrakona, Gerbeta, Daspur, Keshpur, Aushgram, Memari, Ketugram, Raina, Taldangra, Kotulpur, Patrasayar, and Joypur. For the purpose of study, these blocks are coded as to B1 to B16. A multistage sampling procedure was adopted to select potato-growing farmers from the above four major potato-producing districts of West Bengal. Fig.1 illustrates the study area.

Data Collection and Constraint Identification

Fifteen major constraints related to potato cultivation and storage were identified through focus group discussions and expert

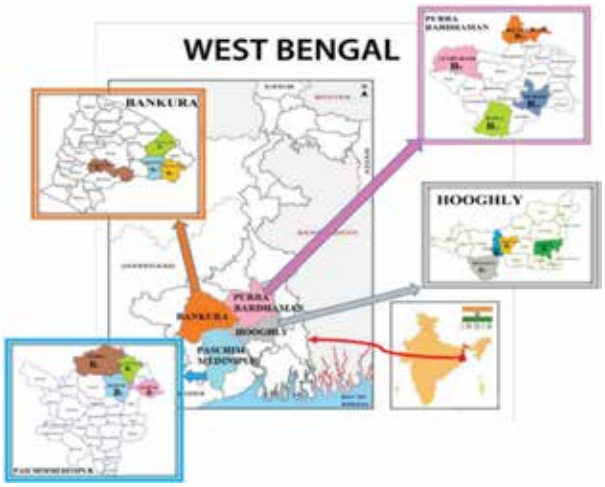

Fig. 1. Study area

interviews. 1 to 10 scale data corresponding to these fifteen identified constraints, along with four response variables severity, occurrence, detection, and environmental impact were collected through a survey conducted among 400 farmers, comprising 25 farmers from each of the 16 blocks within the study area.

The use of a common 1–10 scale also facilitates the aggregation of heterogeneous farmers' perceptions. Since the purpose of the scoring was to establish the relative importance and comparative performance of the constraints rather than to measure an absolute physical quantity, the numerical values were treated as structured preference ratings. Thus, the 1–10 scale provides a transparent and reproducible mechanism for transforming farmers' linguistic judgments into a standardized decision matrix for constraint prioritization.

The fifteen identified constraints and the four response variables were considered as alternatives and criteria, respectively, for constructing decision matrix. These constraints (alternatives) and response variables (criteria) are denoted as A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}, A_{15} and C_1, C_2, C_3, C_4, respectively, for

further analysis. The detailed descriptions of the constraints are presented in Table 1. A brief description of the criteria has been presented in Table 2.

Statistical analysis on the survey data

To improve recommendations from land suitability analysis to yield prediction, multiple area-specific criteria should be considered. Besides key factors like soil, water, fertilizer, and seasonal variations, additional aspects such as proximity to research institutes, markets, roads, and agro-centres are also important. Considering these factors requires an effective prediction approach; thus, multi-dimensional analysis on agriculture data is the most suitable for such complex evaluations (Ahrari *et al.*, 2024; Deepa *et al.*, 2020; Divya *et al.*, 2021;

Table 1. Constraints in potato cultivation and storage with responses from 400 respondents.

Types of Constraints	Constraints Number	Constraint's Description	Frequency	Percentages (%)	Input data Matrix X_n
Cultivation	A_1	Ensuring availability of high-quality seeds at reasonable prices.	366	91.50	X_1
	A_2	Farmers face low and unpredictable prices during peak harvest periods.	277	69.25	X_2
	A_3	Preventing pest and disease.	285	71.25	X_3
	A_4	Farmers face yield losses and crop failure risks from moisture stress driven by unreliable rainfall.	328	82.00	X_4
	A_5	Inadequate irrigation infrastructure.	79	19.75	X_5
	A_6	Insufficient farmer training centres.	87	21.75	X_6
	A_7	Limited and costly access to pesticides and fertilizers when most needed.	269	67.25	X_7
	A_8	Weed overgrowth.	85	21.25	X_8
	A_9	Labour scarcity.	255	63.75	X_9
	A_{10}	Soil nutrient management & technology.	167	41.75	X_{10}
Storage	A_{11}	Inadequate modern cold storage infrastructure.	301	75.25	X_{11}
	A_{12}	Cold storage charge	311	77.25	X_{12}
	A_{13}	Inadequate transport infrastructure.	181	45.25	X_{13}
	A_{14}	Pest attack in storage.	67	16.75	X_{14}
	A_{15}	Efficient cold storage management & technology.	87	21.75	X_{15}

Table 2. Description of the Criteria

Criterion	Code	Description
Severity	C_1	Severity refers to the extent of crop damage or yield loss caused by a particular constraint. It explains the level of impact on potato yield and edible quality. Severity is considered a non-beneficial (cost) criterion in this study.
Occurrence	C_2	Occurrence represents the likelihood or probability of a particular constraint arising. It indicates how frequently a constraint is expected to occur. Like severity, occurrence is also a non-beneficial (cost) criterion in the algorithm.
Detection	C_3	Detection reflects the effectiveness of preventive and maintenance measures against a given constraint. It indicates the ability to identify or prevent the occurrence of a problem. Thus, a higher detection score represents better detectability and is treated as a beneficial criterion for this study.
Environmental impact	C_4	Environmental impact refers to the adverse environmental effects resulting from the use of fertilizers and pesticides. It encompasses factors such as water and air pollution, soil degradation, and nutrient runoff (sulphur, nitrogen, and phosphorus) that lead to the contamination of freshwater and eutrophication. This is also considered a non-beneficial criterion in the study.

Piekutowska et al., 2021; Raghav et al., 2025). For the present study following statistical measures have been computed for the analyse of potato cultivation and storage constraints.

Input data matrix

Primary data were collected from 400 farmers across sixteen major potato-growing blocks in four districts of West Bengal. Fifteen major potato cultivation and storage constraints were identified through focus group discussions, expert opinions, and farmer cooperation. Each constraint includes four response variables as severity, occurrence, detection and environmental impact rated on a 1–10 scale, forming one input data matrix. Hence, fifteen constraints yield fifteen input data matrices X_1, X_2, X_3 … X_{15}, where each $X_n = [a_{ij}]_{16\times4}$ (n = 1, 2, …, 15). The fifteen-input data matrix of the constraints along with 1 to 10 scale data reported by the farmers are presented in Table 3.

Mean vector

Mean vector ($\overline{X}_n$) corresponding to input data matrix is formed in the following way.

$$\overline{X}_n = \frac{1}{p} X_n^T \cdot I = [\bar{a}_j]_{4\times1} \quad \ldots\ldots (1)$$

$$X_n = [a_{ij}]_{16\times4} \quad \ldots\ldots (2)$$

Where the sample size which is equal to sixteen (number of blocks) and I is the unit column matrix of 16 rows. Average value of the j_{th} response variable is $\bar{a}j$.

Covariance Matrix

Covariance matrix $\overline{X}_n$ corresponding to the input data matrix $\overline{X}_n$ is formed in the following way.

Table 3. Survey data with 1 to 10 scale to form input data matrix

Input data matrix	Response variables	Blocks															
		B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	B_{10}	B_{11}	B_{12}	B_{13}	B_{14}	B_{15}	B_{16}
X_1	Severity	7	9	8	9	6	9	8	8	7	7	9	9	6	9	9	8
	Occurrence	7	8	6	6	5	4	6	8	5	4	7	6	7	5	7	5
	Detection	5	4	3	4	6	4	3	3	5	4	3	4	5	3	5	3
	Environmental impact	6	7	5	6	5	6	5	4	6	5	5	6	4	6	7	4
X_2	Severity	6	7	4	3	5	6	4	5	5	4	3	7	6	7	4	4
	Occurrence	8	6	5	4	7	8	6	4	7	5	6	5	7	5	7	6
	Detection	9	5	6	4	6	8	5	5	8	4	8	4	8	4	6	7
	Environmental impact	5	6	5	5	6	5	4	5	4	4	4	5	4	5	6	4
X_3	Severity	8	6	5	6	8	9	7	6	8	5	9	7	6	8	6	8
	Occurrence	7	5	6	8	4	7	5	6	8	5	5	6	7	5	7	5
	Detection	6	4	3	4	3	5	4	3	4	6	3	3	4	5	3	4
	Environmental impact	6	5	4	5	5	6	3	5	5	5	5	6	4	6	5	4
X_4	Severity	10	9	8	9	10	7	10	9	8	9	10	8	9	10	9	9
	Occurrence	5	4	3	4	4	5	3	4	6	3	3	4	5	3	4	4
	Detection	4	3	2	4	3	3	3	5	5	2	2	3	2	2	3	2
	Environmental impact	6	5	4	5	5	6	5	3	5	4	5	5	4	5	6	4
X_5	Severity	6	4	3	7	5	5	4	6	7	4	4	5	5	6	4	5
	Occurrence	5	3	4	4	3	6	3	4	4	6	5	3	3	4	3	4
	Detection	3	4	2	4	5	3	2	2	4	2	3	2	3	3	4	2
	Environmental impact	4	5	3	5	4	4	4	3	5	3	4	5	3	5	6	3

Input data matrix	Response variables	Blocks															
		B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	B_{10}	B_{11}	B_{12}	B_{13}	B_{14}	B_{15}	B_{16}
X_6	Severity	7	6	8	5	5	4	7	6	6	7	5	5	8	5	6	6
	Occurrence	5	3	3	4	5	4	3	5	4	4	3	5	6	3	3	4
	Detection	4	3	2	2	4	3	3	4	2	5	2	2	3	3	4	2
	Environmental impact	5	4	3	4	5	4	5	3	5	5	4	4	4	5	6	4
X_7	Severity	8	6	7	7	5	9	6	8	7	7	8	6	7	7	8	6
	Occurrence	7	5	6	7	6	5	6	6	7	5	8	5	5	6	7	5
	Detection	3	4	2	3	5	2	2	3	3	4	2	3	4	2	3	3
	Environmental impact	5	6	4	5	4	5	4	4	5	4	4	5	3	5	4	4
X_8	Severity	8	7	6	9	8	6	5	5	8	7	6	8	9	6	7	7
	Occurrence	5	3	4	4	3	3	6	5	3	5	3	4	4	5	3	4
	Detection	3	4	2	3	3	4	4	2	2	3	4	2	3	4	3	2
	Environmental impact	4	6	4	5	4	5	4	3	4	5	4	5	4	5	6	3
X_9	Severity	7	5	6	7	8	5	5	4	7	6	7	5	5	7	6	6
	Occurrence	6	4	5	4	6	5	7	4	4	5	6	4	5	4	6	5
	Detection	4	3	2	3	3	4	2	3	4	2	3	4	2	3	4	2
	Environmental impact	5	6	3	5	4	5	4	4	5	4	4	5	3	5	6	4
X_{10}	Severity	6	5	4	5	3	7	5	4	6	5	7	3	5	6	4	5
	Occurrence	5	4	3	5	4	4	3	5	3	4	3	3	5	5	4	4
	Detection	4	5	4	3	5	4	3	5	3	4	3	3	5	5	4	4
	Environmental impact	5	6	4	5	5	6	5	4	4	3	4	4	3	6	5	3
X_{11}	Severity	8	7	9	8	8	9	7	9	6	5	6	7	5	6	5	7
	Occurrence	7	5	6	6	5	7	6	5	7	4	8	6	7	5	5	7
	Detection	5	3	4	4	3	3	5	5	4	4	3	3	5	5	4	4
	Environmental impact	6	5	5	6	4	5	4	3	5	5	3	5	4	6	6	3
X_{12}	Severity	6	4	3	5	6	7	4	5	6	7	5	5	4	3	6	4
	Occurrence	5	3	4	4	6	3	3	4	5	3	5	4	3	4	4	4
	Detection	4	6	3	3	4	5	3	3	5	6	3	3	4	5	3	4
	Environmental impact	5	6	4	5	5	4	4	3	4	4	5	4	3	5	5	3
X_{13}	Severity	7	5	6	8	5	6	5	7	5	6	6	7	5	8	5	5
	Occurrence	5	4	6	3	7	4	6	5	5	7	4	4	6	4	5	5
	Detection	3	4	2	3	2	4	5	2	2	3	3	4	2	5	2	2
	Environmental impact	5	5	3	4	4	5	5	4	5	4	4	5	4	3	4	3
X_{14}	Severity	6	4	6	5	4	6	7	4	4	5	5	6	4	5	4	6
	Occurrence	5	4	3	4	5	3	5	4	3	4	4	5	3	3	5	4
	Detection	4	3	2	5	3	2	3	2	3	4	2	5	2	2	3	3
	Environmental impact	4	6	5	5	4	5	3	5	4	3	3	5	3	5	5	4
X_{15}	Severity	7	6	5	8	5	5	6	7	5	6	6	7	5	6	7	5
	Occurrence	5	3	4	4	6	3	3	4	5	3	4	4	6	3	3	4
	Detection	4	6	3	3	4	4	5	3	4	5	3	4	4	5	3	4
	Environmental impact	5	6	4	4	5	4	4	4	5	4	3	4	3	4	5	3

$$\bar{\bar{X}}_n = \frac{1}{P-1} X_{n*}^T X_{n*} = [b_{ij}]_{4\times4} \quad \ldots. (3)$$

Where X_{n^*} is another matrix,

$$X_{n*} = [\, c_{ij} \,]_{16\times4}, \; c_{ij} = a_{ij} - \bar{a}_j \quad \ldots (4)$$

Diagonal and off diagonal elements of the covariance matrix are the variance and covariance of the response variables, b_{jj} is the variance of j_{th} variable.

Standard deviation of j_{th} variable, $s_j = \sqrt{bjj}$ ……. … (5)

The standard deviation vector, $Sn = [S_j]_{4\times1}$ ……..…. (6)

Correlation Matrix

Correlation matrix corresponding to input data matrix is formed in the following way.

$\tilde{X}_n$ is the correlation matrix of the data matrix X_n,

$$\tilde{X}_n = [d_{ij}]_{4\times4} \quad \ldots\ldots\ldots\ldots (7)$$

$$d_{ij} = \frac{b_{ij}}{s_i \times s_j} \quad \ldots\ldots\ldots\ldots (8)$$

$$\frac{b_{jj}}{s_{j\times s_j}} = 1 \quad \ldots\ldots\ldots\ldots (9)$$

Hypothesis testing for mean value and mean vector

Hypothesis is the statement that has to be proven.

H_o and H_1 are the null and alternative hypothesis respectively.

$$H_o : \bar{a}_j = \bar{\mu}_j \quad \ldots. (10)$$

$$H_1 : \bar{a}_j \neq \bar{\mu}_j \quad \ldots (11)$$

$\bar{a}_j$ and $\bar{\mu}_j$ are mean value of the j_{th} response variable for the sample and population respectively.

Confidence interval or CI

θ is the statistic,

$$\theta = \frac{\bar{a}_j - \bar{\mu}_j}{\frac{s_j}{\sqrt{P}}} \quad \ldots. (12)$$

Where, s_j is the sample standard deviation of j_{th} response variable and P is the sample size.

CI will be,

$$-Z_{\alpha/2} \leq \theta \leq Z_{\alpha/2} \quad \ldots\ldots (13)$$

The critical value of $Z_{\alpha/2}$ will be taken from suitable statistical distribution table.

$$-Z_{\alpha/2} \leq \frac{\bar{a}_j - \bar{\mu}_j}{\frac{s_j}{\sqrt{P}}} \leq Z_{\alpha/2} \quad \ldots\ldots\ldots (14)$$

$$\bar{a}_j - \frac{Z_{\alpha/2}\, s_j}{\sqrt{P}} \leq \bar{\mu}_j \leq \bar{a}_j + \frac{Z_{\alpha/2}\, s_j}{\sqrt{P}} \quad \ldots\ldots (15)$$

Mean vector hypothesis test

H_{on} and H_{1n} are the null and alternative hypothesis of the input data matrix , n = 1,2,3, 4……14,15.

$$H_{on}: \bar{X}_n = \bar{\mu}_n \quad \ldots. (16)$$

$$H_{1n}: \bar{X}_n \neq \bar{\mu}_n \quad \ldots (17)$$

$\bar{X}_n$ and $\bar{\mu}_n$ are the mean vector of sample size and population respectively.

CI will be,

$$\bar{X}_n - \frac{Z_{\alpha/2}}{\sqrt{P}} . S_n \leq \bar{\mu}_n \leq \bar{X}_n + \frac{Z_{\alpha/2}}{\sqrt{P}} . S_n \quad \ldots (18)$$

S_n is the standard deviation vector of the sample.

As P is the sample size = 16 which is less than 30 and non-directional hypothesis testing two tail t- distribution is suitable. α is the level of significance. $\alpha/2$ will be affected in each side of the confidence interval. $Z_{\alpha/2}$ is the critical value in the confidence interval and will be selected from t- distribution table with proper degree of freedom, degree freedom = sample size – 1. Assumed α = 0.1, $\alpha/2$ = 0.05 and degree of freedom = 16-1 = 15. From the t-distribution table $Z_{\alpha/2}$ = 2.13.

Ranking of the constraints

Failure mode and effects analysis (FMEA) is widely used in reliability studies, where severity (S), occurrence (O), and detectability (D) are combined to form the risk priority number (RPN) (Zandi et al., 2020). The concept of (FMEA) was extended to the agricultural project risk management by

dividing severity, occurrence, detection and environmental impact. A hybrid model was developed by integrating multiple-criteria decision-making (MCDM) of TOPSIS with the analytic hierarchy process (AHP) and fuzzy set theory to provide decision support for selecting sustainable solutions to agricultural challenges (Keshavarzi et al., 2020; Rouyendegh & Savalan 2020). The fifteen constraints (alternatives) have been ranked with the help of Fuzzy AHP (Analytic Hierarchy Process) and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method. The response variables (criteria) are as severity, occurrence, detection and environmental impact. The weight vector of these response variables is calculated by the help of Fuzzy AHP method whereas the rank of the constraints is found out using TOPSIS.

Determination of criteria weights using triangular Fuzzy numbers.

The criteria weights have been determined by the following steps.

Step 1. Determine fuzzy geometric mean value.

P is the number of criteria; each criterion is denoted by a triangular Fuzzy membership number as (l_i, m_i, u_i), where i = 1, 2, 3, ……., P. The geometric mean value of the criteria is denoted by (l_j, m_j, u_j) in triangular Fuzzy number, where j = 1, 2, 3, ……P.

$$(l_j, m_j, u_j) = (l_1 \times l_2 \times l_3 \times \ldots \times l_P)^{\frac{1}{P}}, (m_1 \times m_2 \times m_3 \times \ldots \times m_P)^{\frac{1}{P}}, (u_1 \times u_2 \times u_3 \times \ldots \times u_P)^{\frac{1}{P}} \quad \ldots\ldots (19)$$

Step 2. Determine fuzzy criteria weight.

The weight of the criteria is denoted by (l_{wj}, m_{wj}, u_{wj}) in triangular Fuzzy number.

$$(l_{wj}, m_{wj}, u_{wj}) = (l_j, m_j, u_j) \otimes \left(\frac{1}{\sum_{j=1}^{P} u_j}, \frac{1}{\sum_{j=1}^{P} m_j}, \frac{1}{\sum_{j=1}^{P} l_j}\right) \quad \ldots (20)$$

Step 3. Defuzzification of criteria weight.

The weight of the j_{th} criteria is denoted by w_j in numerical crest value then,

$$w_j = \frac{(l_{wj} + m_{wj} + u_{wj})}{3} \quad \ldots\ldots (21)$$

Step 4. Normalize criteria weight.

The weight in normalized crest value of the j_{th} criteria is $\overline{w}_j$.

$$\overline{w}_j = \frac{w_j}{\sum_{j=1}^{P} w_j} \quad \ldots\ldots (22)$$

Determination of performance score using TOPSIS

The following steps are followed in TOPSIS method.

Step 1. The decision support evaluation matrix $(y_{ij})_{q\times p}$ is formed with q number of alternatives and p number of criteria having as an element of row and column.

Step 2. The $(y_{ij})_{q\times p}$ matrix is normalized to create the normalized decision matrix $(t_{ij})_{q\times p}$, applying the method of normalization, $t_{ij} = \frac{y_{ij}}{\sqrt{\sum_{k=1}^{q} y_{kj}^2}}$, i = 1, 2…...q and j = 1, 2…. p.

Step 3. The weighted normalized decision matrix $(u_{ij})_{q\times p}$ is calculated with the elements of u_{ij} as, $u_{ij} = t_{ij} \times \overline{w}_j$, $\overline{w}_j$ is the normalized weight of j_{th} criteria such that $\sum_{j=1}^{p} \overline{w}_j = 1$.

Step 4. The best and worst value correspond to alternatives of criteria are denoted as and respectively. These values are selected as follows,

u_{bj} = max (u_{ij}), if j_{th} criteria have good impact towards the goal.

u_{bj} = min (u_{ij}), if j_{th} criteria have bad impact towards the goal.

u_{wj} = min (u_{ij}), if j_{th} criteria have good impact towards the goal.

u_{wj} = max (u_{ij}), if j_{th} criteria have bad impact towards the goal.

Step 5. Euclidean distance between best and i_{th} (target) alternatives is denoted by s_i^+ then,

$$s_i^+ = \sqrt{\sum_{j=1}^{p} (u_{ij} - u_{bj})^2}, \; i = 1,2,3\ldots\ldots q.$$

Euclidean distance between worst and (target) alternatives is denoted by s_i^- then,

$$s_i^- = \sqrt{\sum_{j=1}^{P}(u_{ij} - u_{wj})^2},\ i = 1,2,3\ldots\ldots q.$$

Step 6. The score of i_{th} (target) alternative is denoted by S_{ci}.

$$S_{ci} = \frac{s^-}{s^+ + s^-},\ 0 \le S_{ci} \le 1,\ i = 1,2,3\ldots\ldots q.$$

Step 7. Rank the alternatives accordingly to S_{ci}

In TOPSIS, alternatives are ranked according to their distance from the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS).

Ranking rule: A higher indicates that the alternative is closer to the ideal solution and therefore receives a better (higher) rank. A lower indicates lower importance/preference.

RESULTS AND DISCUSSIONS

Mean vector, correlation matrix and standard deviation vector are shown in Table 4. Summary of the statistical results are shown in Table 5. Null hypothesis test has been done to find the mean or average values of criteria of population for each constraint. Permissible maximum and minimum value of severity, occurrence, detection and impact of fifteen constraints are shown in Table 6.

Table 4. Mean vector, Correlation Matrix & Standard Deviation vector.

Mean Vector, $\bar{X}_n$	$[\bar{a}_j]_{4\times1}$	Correlation Matrix $\tilde{X}_n$	$[d_{ij}]_{4\times4}$				Standard Deviation Vector, Sn	$[S_j]_{4\times1}$
$\bar{X}_1$	8.00	$\tilde{X}_1$	1.00	0.15	-0.53	0.51	S_1	1.09
	6.00		0.15	1.00	-0.06	0.06		1.26
	4.00		-0.53	-0.06	1.00	0.29		0.96
	5.44		0.51	0.06	0.29	1.00		0.96
$\bar{X}_2$	5.00	$\tilde{X}_2$	1.00	0.23	-0.35	0.32	S_2	1.37
	6.00		0.23	1.00	0.97	0.07		1.26
	6.06		-0.35	0.97	1.00	-0.30		1.41
	4.81		0.32	0.07	-0.30	1.00		0.75
$\bar{X}_3$	7.00	$\tilde{X}_3$	1.00	-0.08	0.10	0.36	S_3	1.32
	6.00		-0.08	1.00	0.10	0.19		1.21
	4.00		0.10	0.10	1.00	0.31		1.03
	4.94		0.36	0.19	0.31	1.00		0.85
$\bar{X}_4$	9.00	$\tilde{X}_4$	1	-0.42	-0.14	0.00	S_4	0.89
	4.00		-0.42	1.00	0.58	0.27		0.89
	3.00		-0.14	0.58	1.00	0.08		1.03
	4.81		0.00	0.27	0.08	1.00		0.84
$\bar{X}_5$	5.00	$\tilde{X}_5$	1.00	0.06	0.30	0.30	S_5	1.15
	4.00		0.06	1.00	-0.27	-0.33		1.03
	3.00		0.30	0.27	1.00	0.58		0.96
	4.12		0.30	-0.33	0.58	1.00		0.96
$\bar{X}_6$	6.00	$\tilde{X}_6$	1.00	0.12	0.18	-0.08	S_6	1.15
	4.00		0.12	1.00	0.22	-0.17		0.96
	3.00		0.18	0.22	1.00	0.42		0.96
	4.38		-0.08	-0.17	0.42	1.00		0.81

Mean Vector, $\bar{X}_n$	$[\bar{a}_j]_{4\times1}$	Correlation Matrix $\tilde{X}_n$	$[d_{ij}]_{4\times4}$				Standard Deviation Vector, Sn	$[S_j]_{4\times1}$
$\bar{X}_7$	7.00	$\tilde{X}_7$	1.00	0.33	-0.51	0.00	S_7	1.03
	6.00		0.33	1.00	-0.31	0.00		0.96
	3.00		-0.51	-0.31	1.00	-0.11		0.89
	4.44		0.00	0.00	-0.11	1.00		0.73
$\bar{X}_8$	7.00	$\tilde{X}_8$	1.00	-0.33	-0.26	0.18	S_8	1.26
	4.00		-0.33	1.00	0.00	-0.32		0.96
	3.00		-0.26	0.00	1.00	0.45		0.82
	4.44		0.18	-0.32	0.45	1.00		0.89
$\bar{X}_9$	6.00	$\tilde{X}_9$	1.00	0.19	0.14	0.07	S_9	1.10
	5.00		0.19	1.00	-0.17	-0.23		0.96
	3.00		0.14	-0.17	1.00	0.72		0.82
	4.50		0.07	-0.23	0.72	1.00		0.89
$\bar{X}_{10}$	5.00	$\tilde{X}_{10}$	1.00	0.07	-0.20	0.21	S_{10}	1.21
	4.00		0.07	1.00	0.59	0.15		0.82
	4.00		-0.20	0.59	1.00	0.15		0.82
	4.50		0.21	0.15	0.15	1.00		1.03
$\bar{X}_{11}$	7.00	$\tilde{X}_{11}$	1.00	0.08	-0.11	-0.09	S_{11}	1.41
	6.00		0.08	1.00	-0.08	-0.28		1.09
	4.00		-0.11	-0.08	1.00	0.08		0.82
	4.69		-0.09	-0.28	0.08	1.00		1.08
$\bar{X}_{12}$	5.00	$\tilde{X}_{12}$	1.00	0.18	0.24	0.06	S_{12}	1.26
	4.00		0.18	1.00	-0.28	0.26		0.89
	4.00		0.24	-0.28	1.00	0.21		1.10
	4.31		0.06	0.26	0.21	1.00		0.87
$\bar{X}_{13}$	6.00	$\tilde{X}_{13}$	1.00	-0.53	0.33	-0.16	S_{13}	1.10
	5.00		-0.53	1.00	-0.37	-0.15		1.15
	3.00		033	-0.37	1.00	0.33		1.10
	4.19		-0.16	-0.15	0.33	1.00		0.75
$\bar{X}_{14}$	5.06	$\tilde{X}_{14}$	1.00	0.16	0.19	-0.09	S_{14}	1.00
	4.00		0.16	1.00	0.56	0.00		0.82
	3.00		0.19	0.56	1.00	0.13		1.03
	4.38		-0.09	0.00	0.13	1.00		0.96
$\bar{X}_{15}$	6.00	$\tilde{X}_{15}$	1.00	-0.27	-0.23	0.16	S_{15}	0.96
	4.00		-0.27	1.00	-0.29	-0.08		1.03
	4.00		-0.23	-0.29	1.00	0.36		0.89
	4.19		0.16	-0.08	0.36	1.00		0.84

Table 5. Summary of the statistical results.

Constraints No.	Sample mean value of response variables ($\bar{a}_j$) j = 1,2,3,4.				Sample standard deviation of response variables (s_j) j = 1,2,3,4.			
	Severity $\bar{a}_1$	Occurrence $\bar{a}_2$	Detection $\bar{a}_3$	Impact $\bar{a}_4$	Severity s_1	Occurrence s_2	Detection s_3	Impact s_4
A_1	8.00	6.00	4.00	5.44	1.09	1.26	0.96	0.96
A_2	5.00	6.00	6.06	4.81	1.37	1.26	1.41	0.75
A_3	7.00	6.00	4.00	4.94	1.32	1.21	1.03	0.85
A_4	9.00	4.00	3.00	4.81	0.89	0.89	1.03	0.84
A_5	5.00	4.00	3.00	4.12	1.15	1.03	0.96	0.96
A_6	6.00	4..00	3.00	4.38	1.15	0.96	0.96	0.81
A_7	7.00	6.00	3.00	4.44	1.03	0.96	0.89	0.73
A_8	7.00	4.00	3.00	4.44	1.26	0.96	0.82	0.89
A_9	6.00	5.00	3.00	4.50	1.10	0.96	0.82	0.89
A_{10}	5.00	4.00	4.00	4.50	1.21	0.82	0.82	1.03
A_{11}	7.00	6.00	4.00	4.69	1.41	1.09	0.82	1.08
A_{12}	5.00	4.00	4.00	4.31	1.26	0.89	1.10	0.87
A_{13}	6.00	5.00	3.00	4.19	1.10	1.15	1.10	0.75
A_{14}	5.06	4.00	3.00	4.38	1.00	0.82	1.03	0.96
A_{15}	6.00	4.00	4.00	4.19	0.96	1.03	0.89	0.84

Table 6. Hypothesis testing results.

Constraints No.	Null Hypothesis H_{on}: $\bar{a}_j = \bar{\mu}_j$	Population mean value ($\bar{\mu}_j$) of response variables for null hypothesis			
		Severity $\bar{\mu}_1$	Occurrence $\bar{\mu}_2$	Detection $\bar{\mu}_3$	Impact $\bar{\mu}_4$
A_1	H_{01}	$7.42 \le \bar{\mu}_1 \le 8.58$	$5.33 \le \bar{\mu}_2 \le 6.67$	$3.49 \le \bar{\mu}_3 \le 4.51$	$4.93 \le \bar{\mu}_4 \le 5.95$
A_2	H_{02}	$4.30 \le \bar{\mu}_1 \le 5.70$	$5.33 \le \bar{\mu}_2 \le 6.67$	$5.25 \le \bar{\mu}_3 \le 6.75$	$4.41 \le \bar{\mu}_4 \le 5.21$
A_3	H_{03}	$6.30 \le \bar{\mu}_1 \le 7.70$	$5.36 \le \bar{\mu}_2 \le 6.64$	$3.45 \le \bar{\mu}_3 \le 4.55$	$4.49 \le \bar{\mu}_4 \le 5.39$
A_4	H_{04}	$8.53 \le \bar{\mu}_1 \le 9.47$	$3.53 \le \bar{\mu}_2 \le 4.47$	$2.45 \le \bar{\mu}_3 \le 3.55$	$4.36 \le \bar{\mu}_4 \le 5.26$
A_5	H_{05}	$4.39 \le \bar{\mu}_1 \le 5.61$	$3.45 \le \bar{\mu}_2 \le 4.55$	$2.49 \le \bar{\mu}_3 \le 3.51$	$3.61 \le \bar{\mu}_4 \le 4.63$
A_6	H_{06}	$5.39 \le \bar{\mu}_1 \le 6.61$	$3.49 \le \bar{\mu}_2 \le 4.51$	$2.49 \le \bar{\mu}_3 \le 3.51$	$3.95 \le \bar{\mu}_4 \le 4.81$
A_7	H_{07}	$6.45 \le \bar{\mu}_1 \le 7.55$	$5.49 \le \bar{\mu}_2 \le 6.51$	$2.53 \le \bar{\mu}_3 \le 3.47$	$4.04 \le \bar{\mu}_4 \le 4.83$
A_8	H_{08}	$6.33 \le \bar{\mu}_1 \le 7.67$	$3.49 \le \bar{\mu}_2 \le 4.51$	$2.56 \le \bar{\mu}_3 \le 3.44$	$3.97 \le \bar{\mu}_4 \le 4.91$
A_9	H_{09}	$5.41 \le \bar{\mu}_1 \le 6.59$	$4.49 \le \bar{\mu}_2 \le 5.51$	$2.56 \le \bar{\mu}_3 \le 3.44$	$4.03 \le \bar{\mu}_4 \le 4.97$
A_{10}	H_{010}	$4.36 \le \bar{\mu}_1 \le 5.64$	$3.56 \le \bar{\mu}_2 \le 4.44$	$3.36 \le \bar{\mu}_3 \le 4.44$	$3.95 \le \bar{\mu}_4 \le 5.05$
A_{11}	H_{011}	$6.25 \le \bar{\mu}_1 \le 7.75$	$5.42 \le \bar{\mu}_2 \le 6.58$	$3.56 \le \bar{\mu}_3 \le 4.44$	$4.11 \le \bar{\mu}_4 \le 5.27$
A_{12}	H_{012}	$4.33 \le \bar{\mu}_1 \le 5.67$	$3.53 \le \bar{\mu}_2 \le 4.47$	$3.41 \le \bar{\mu}_3 \le 4.59$	$3.85 \le \bar{\mu}_4 \le 4.77$
A_{13}	H_{013}	$5.41 \le \bar{\mu}_1 \le 6.59$	$4.39 \le \bar{\mu}_2 \le 5.61$	$2.41 \le \bar{\mu}_3 \le 3.59$	$3.79 \le \bar{\mu}_4 \le 4.59$
A_{14}	H_{014}	$4.53 \le \bar{\mu}_1 \le 5.59$	$3.56 \le \bar{\mu}_2 \le 4.44$	$2.45 \le \bar{\mu}_3 \le 3.55$	$3.87 \le \bar{\mu}_4 \le 4.89$
A_{15}	H_{015}	$5.49 \le \bar{\mu}_1 \le 6.51$	$3.45 \le \bar{\mu}_2 \le 4.55$	$3.53 \le \bar{\mu}_3 \le 4.47$	$3.75 \le \bar{\mu}_4 \le 4.64$

Determination of criteria weights using Fuzzy-AHP.

Using Fuzzy-AHP the weights of the criteria have been determined following the various steps mentioned above.

Thus, the determined weights are shown in Table 7. Severity, occurrence, detection and impact are weighted as 34%, 31% ,13% and 22% respectively.

Application of TOPSIS for ranking of the constraints.

Decision support evaluation matrix of the TOPSIS method have been formed with fifteen constraints (alternatives) as rows and four response variables (criteria) as columns. Severity, occurrence, detection and environmental impact are the response variables and the value of these response variables for a particular constraint has been taken from the mean vector of that constraint. Table 8 and Table 9 show the decision and normalized decision matrix whereas weighted normalized matrix and TOPSIS result are shown in Table 10 and Table 11 respectively. TOPSIS result shows that the constraint-1 which is accessing quality seeds at affordable price becomes a top most serious constraint. Disease free good quality potato seeds are the most essential input for growing healthy and sustainable crops. Potato being a propagated clonally crop a rapid rate of perversive degeneration cause the potato seed to highly deteriorate after two or three generation for continuing amassing of viral and biotic diseases as a result most of the farmers in West Bengal depend on reliable outside source. Traditionally the farmers of West Bengal depend on Punjab as a reliable source of disease-free quality potato seeds which increases the cost of cultivation adding an extra financial burden.

Table 7. Determination of criteria weight

Pair- wise comparison of the criteria with triangular Fuzzy membership number.				
Criteria	Severity	Occurrence	Detection	Impact
Severity	(1,1,1)	(1,2,3)	(2,3,4)	(1,1,1)
Occurrence	(1/3, 1/2,1)	(1,1,1)	(1,2,3)	(1,2,3)
Detection	(1/4,1/3,1/2)	(1/3, 1/2,1)	(1,1,1)	(1/3, 1/2,1)
Impact	(1,1,1)	(1/3, 1/2,1)	(1,2,3)	(1,1,1)

	Weight of the criteria in triangular Fuzzy membership number. (l_{wj}, m_{wj}, u_{wj})		
Criteria		Criteria	
Severity	(1.189, 1.565, 1.861)	Severity	(0.346, 0.370, 0.324)
Occurrence	(1.074, 1.189, 1.732)	Occurrence	(0.313, 0.363, 0.277)
Detection	(0.408, 0.537, 0.841)	Detection	(0.119, 0.125, 0.146)
Impact	(0.759, 1.00, 1.316)	Impact	(0.220, 0.233, 0.229)

Weight of the criteria in numerical crest value (W_j). Defuzzification		Normalized weight of the criteria in numerical crest value ($\overline{W}_j$).	
Criteria		Criteria	
Severity	0.347	Severity	0.34
Occurrence	0.318	Occurrence	0.31
Detection	0.13	Detection	0.13
Impact	0.224	Impact	0.22

Table 8. Decision Matrix $(Y_{ij})_{15\times4}$

Alternatives	Criteria			
	Severity	Occurrence	Detection	Impact
A_1	8.00	6.00	4.00	5.44
A_2	5.00	6.00	6.06	4.81
A_3	7.00	6.00	4.00	4.94
A_4	9.00	4.00	3.00	4.81
A_5	5.00	4.00	3.00	4.12
A_6	6.00	4.00	3.00	4.38
A_7	7.00	6.00	3.00	4.44
A_8	7.00	4.00	3.00	4.44
A_9	6.00	5.00	3.00	4.50
A_{10}	5.00	4.00	4.00	4.50
A_{11}	7.00	6.00	4.00	4.69
A_{12}	5.00	4.00	4.00	4.31
A_{13}	6.00	5.00	3.00	4.19
A_{14}	5.06	4.00	3.00	4.38
A_{15}	6.00	4.00	4.00	4.19

Table 9. Normalized decision matrix $(t_{ij})_{15\times3}$

Alternatives	Criteria			
	Severity	Occurrence	Detection	Impact
A_1	0.324	0.317	0.280	0.308
A_2	0.202	0.317	0.424	0.273
A_3	0.283	0.317	0.280	0.280
A_4	0.364	0.211	0.210	0.273
A_5	0.202	0.211	0.210	0.234
A_6	0.243	0.211	0.210	0.248
A_7	0.283	0.317	0.210	0.252
A_8	0.283	0.211	0.210	0.252
A_9	0.243	0.264	0.210	0.255
A_{10}	0.202	0.211	0.280	0255
A_{11}	0.283	0.317	0.280	0.266
A_{12}	0.202	0.211	0.280	0.244
A_{13}	0.243	0.264	0.210	0.238
A_{14}	0.205	0.211	0.210	0.248
A_{15}	0.243	0.211	0.280	0.238
Weight $(\overline{W}_j)$	0.34	0.31	0.13	0.22
= , i = 1, 2…...15 and j = 1, 2,3,4.				

Table 10. Weighted normalized decision matrix $(u_{ij})_{15\times3}$

Alternatives	Criteria			
	Severity	Occurrence	Detection	Impact
A_1	0.110	0.0983	0.0363	0.0678
A_2	0.0688	0.0983	0.0551	0.0600
A_3	0.0963	0.0983	0.0363	0.0620
A_4	0.1238	0.0655	0.0273	0.0600
A_5	0.0688	0.0655	0.0273	0.0514
A_6	0.0826	0.0655	0.0273	0.0546
A_7	0.0963	0.0983	0.0273	0.0554
A_8	0.0963	0.0655	0.0273	0.0554
A_9	0.0826	0.0819	0.0273	0.0561
A_{10}	0.0688	0.0655	0.0363	0.0561
A_{11}	0.0963	0.0983	0.0363	0.0585
A_{12}	0.0688	0.0655	0.0363	0.0537
A_{13}	0.0826	0.0819	0.0273	0.0523
A_{14}	0.0696	0.0655	0.0273	0.0546
A_{15}	0.0826	0.0655	0.0363	0.0523
u_{bj}	0.0688	0.0655	0.0551	0.0513
u_{wj}	0.1238	0.0983	0.0273	0.0678

Table 11. TOPSIS result.

Sl. No.	Alternatives	s_i^-	s_i^+	s_{ci} (Score)	Rank
01	A_1	0.0290	0.0583	0.3320	15
02	A_2	0.0289	0.0339	0.4603	13
03	A_3	0.0561	0.0478	0.5400	9
04	A_4	0.0533	0.0623	0.4612	12
05	A_5	0.0458	0.0278	0.6225	5
06	A_6	0.0448	0.0312	0.5895	7
07	A_7	0.0431	0.0512	0.4572	14
08	A_8	0.0653	0.0393	0.6240	4
09	A_9	0.0341	0.0354	0.4907	10
10	A_{10}	0.0657	0.0193	0.7730	3
11	A_{11}	0.0433	0.0472	0.4782	11
12	A_{12}	0.0655	0.0189	0.7765	2
13	A_{13}	0.0471	0.0351	0.5729	8
14	A_{14}	0.1288	0.0280	0.8214	1
15	A_{15}	0.0374	0.0232	0.6167	6

The present study prioritised fifteen major constraints affecting potato cultivation and storage in four important potato-producing districts of West Bengal using a Fuzzy-AHP–TOPSIS framework. The Fuzzy-AHP results assigned the highest weight to severity (0.34), followed by occurrence (0.31), environmental impact (0.22) and detection (0.13). These weights indicate that the perceived seriousness of a constraint and the frequency with which it occurs are the dominant dimensions influencing farmers' overall assessment. Environmental consequences also received substantial importance, whereas detection received comparatively lower weight. Thus, the ranking obtained from TOPSIS reflects not only how frequently a constraint occurs but also its perceived seriousness and broader impact.

The TOPSIS results show substantial differences among the fifteen constraints. A14 (pest attack during storage) obtained the highest TOPSIS score of 0.8214 and was ranked 1st, indicating the most favourable or least critical position under the adopted ranking convention. Conversely, A1 (access to quality seeds at affordable prices) recorded the lowest score of 0.3320 and was ranked 15th, identifying it as the most critical constraint. The large difference between these two scores demonstrates that farmers do not perceive all constraints as equally important and that interventions should therefore be prioritised according to their relative criticality.

Access to quality seed as the most critical constraint

The most important finding is the 15th rank of A1, concerning access to quality seed at reasonable prices. Although the constraint is essentially an input-related problem, its consequences extend across the entire production cycle. Seed quality determines crop establishment, plant vigour, disease susceptibility, tuber development and final productivity. Moreover, the high frequency of this constraint reported by 366 out of 400 farmers (91.50%) in the survey, provides strong evidence that it is a widespread problem rather than a localised concern.

The high severity and occurrence associated with A1 are particularly important because these two criteria together account for 65% of the total Fuzzy-AHP weight. Therefore, even where detection is relatively easier, the high severity and frequent occurrence of the seed problem substantially influence its overall priority. The finding suggests that improving access to certified or high-quality seed at affordable prices should be considered a first-line intervention for improving potato productivity in the study area.

Market-price instability

A2, low and unpredictable prices during peak harvesting periods, was ranked 13th, with a TOPSIS score of 0.4603. Although its TOPSIS score is higher than that of A1, the constraint remains an important economic concern. About 69.25% of respondents identified unstable or low prices as a problem.

The problem is particularly relevant because potato production is seasonal and large quantities of tubers reach the market within a relatively short period. When supply exceeds immediate market demand, farm-gate prices may decline sharply. Farmers who lack adequate storage facilities or financial capacity to delay sales are consequently compelled to sell during periods of low prices. Thus, market-price instability is closely interconnected with the storage constraints identified in the study. Strengthening storage access, market information systems, farmer-producer organisations and alternative marketing channels could reduce farmers' dependence on distress sales.

Pest and disease management

A3, pest and disease control, obtained a TOPSIS score of 0.5400 and was ranked 9th. Its relatively high occurrence, identified by 71.25% of farmers, shows that biological stresses remain a significant production concern. Pest and disease attacks can reduce both yield and tuber quality and can increase expenditure on pesticides.

The moderate ranking of A3 should not be interpreted as indicating that pest and disease problems are unimportant. Rather, compared with constraints such as seed availability and market conditions, farmers appear to experience pest and disease management as a comparatively less dominant constraint in the overall decision structure. The comparatively high severity values observed across several blocks indicate that local climatic conditions, cropping practices and availability of plant-protection services may influence the perceived importance of this constraint.

Erratic rainfall and moisture stress

A4, unreliable rainfall causing moisture stress and yield-loss risk, received a TOPSIS score of 0.4612 and ranked 12th. However, its reported frequency of 82% makes it one of the most widely experienced constraints in the survey. This apparently contrasting result is important. High occurrence does not automatically result in the highest overall priority because TOPSIS simultaneously considers severity, occurrence, detection and environmental impact.

The block-wise responses show considerable variation in the perception of rainfall-related stress. This variation is expected because access to irrigation, soil characteristics, local rainfall patterns and farmers' ability to supplement rainfall through irrigation differ between blocks. Areas with comparatively inadequate irrigation infrastructure are likely to be more vulnerable to irregular rainfall. Consequently, climate-risk management should be combined with irrigation development rather than addressed through a single intervention.

Irrigation and farmer training

A5, inadequate irrigation infrastructure, was ranked 5th with a score of 0.6225. Its relatively low reported frequency (19.75%) suggests that irrigation infrastructure is not uniformly perceived as a major constraint across all surveyed locations. Nevertheless, where it exists, its consequences can be substantial, particularly during periods of inadequate rainfall.

Similarly, A6, insufficient farmer training centres, was ranked 7th, with a score of 0.5895. Its frequency was only 21.75%, indicating substantial spatial variation. The block-wise responses suggest that farmers' access to training and technical support differs between locations. Such variation is important because improved knowledge concerning seed selection, disease management, irrigation scheduling, fertiliser application, weed control and storage practices can reduce the severity of several other constraints simultaneously.

Cost and availability of agricultural inputs

A7, limited and costly access to pesticides and fertilisers at critical stages, received a score of 0.4572 and ranked 14th. Despite its relatively low TOPSIS position, its occurrence among 67.25% of farmers demonstrates that input accessibility is widespread.

The result suggests that farmers frequently encounter input-related difficulties, but the overall severity of these difficulties may be lower than that associated with quality seed. Nevertheless, timely availability is crucial because delayed application of fertilisers

or plant-protection chemicals can reduce their effectiveness and increase production risk. Input availability should therefore be considered together with extension services, credit access and seasonal supply planning.

Weed infestation, labour scarcity and soil management

A8, weed overgrowth, obtained a score of 0.6240 and ranked 4th. Although only 21.25% of farmers reported it as a major constraint, the relatively favourable TOPSIS position indicates that, among the constraints considered, it is less critical overall. Nevertheless, weed infestation can compete with potato plants for nutrients, water and sunlight and can increase labour and production costs.

A9, labour scarcity, ranked 10th, with a score of 0.4907, and was reported by 63.75% of respondents. The high occurrence indicates that labour availability is an important operational issue, even though its aggregate TOPSIS position is lower than several other constraints. Labour shortages may become particularly important during planting, intercultural operations and harvesting, when delays can directly influence yield and quality.

A10, soil nutrient management and technology, achieved a score of 0.7730 and ranked 3rd. This comparatively high TOPSIS score indicates a relatively favourable position, although the issue remains agronomically relevant. The finding suggests that, compared with the most critical constraints, farmers may have greater ability to manage soil nutrient-related problems through existing practices or advisory support.

Storage-related constraints

The storage-related findings provide an important dimension of the study. A11, inadequate modern cold-storage infrastructure, scored 0.4782 and ranked 11th, whereas A12, cold-storage charges, obtained 0.7765 and ranked 2nd. The difference between these two results is noteworthy. It suggests that although infrastructure availability is a concern, the relative economic burden associated with storage charges may be perceived differently across the surveyed locations.

The high score of A12 indicates a comparatively favourable position under the adopted TOPSIS convention. However, the fact that 77.25% of farmers reported cold-storage charges as a constraint demonstrates that the issue is widespread. This apparent difference between frequency and TOPSIS position again illustrates the importance of using a multi-criteria approach rather than ranking constraints solely according to the number of farmers reporting them.

A13, inadequate transport infrastructure, obtained a score of 0.5729 and ranked 8th. Transport facilities are particularly important because potatoes are bulky and perishable commodities, and transportation costs directly affect the profitability of farmers and traders. Poor rural roads and inadequate transport facilities can increase post-harvest losses, delay delivery and reduce farmers' access to distant markets and storage facilities.

Storage pest attack and cold-storage management

The most favourable constraint was A14, pest attack during storage, with a TOPSIS score of 0.8214 and 1st rank. Only 16.75% of farmers reported this problem, which is the lowest frequency among the fifteen constraints. This agreement between the low reported frequency and high TOPSIS score strengthens the interpretation that storage pest attack is comparatively less critical in the surveyed area.

A15, efficient cold-storage management and technology, received a score of 0.6167 and ranked 6th. The finding indicates that although modern management and technology remain relevant, farmers do not perceive them as the most urgent constraint compared with fundamental production problems such as seed availability.

Block-wise comparison

The block-wise variation is an important outcome because a single district-level intervention may not adequately address the specific needs of individual production clusters. Overall, the block-level findings demonstrate that the **nature and intensity of potato constraints are spatially heterogeneous.** Therefore, the TOPSIS-based overall ranking should be used as a regional priority framework, while block-level scores should guide the intervention.

CONCLUSION

The present study developed a systematic framework for prioritising major constraints affecting potato cultivation and storage in four major potato-producing districts of West Bengal. Fifteen constraints were identified through stakeholder consultations, focus group discussions and expert interactions and were evaluated using four criteria: severity, occurrence, detection and environmental impact. The application of Fuzzy-AHP assigned weights of 0.34, 0.31, 0.13 and 0.22, respectively, demonstrating that severity and occurrence were the two most influential criteria in the decision-making process.

The TOPSIS analysis revealed substantial differences in the relative priority of the identified constraints. Access to quality seed at an affordable price (A1) emerged as the most critical constraint, recording the lowest TOPSIS score of 0.3320 and the 15th position under the adopted ranking convention. Its importance is further supported by the fact that 91.50% of surveyed farmers reported this constraint. This finding establishes affordable access to quality seed as a fundamental intervention point for improving potato productivity and reducing production risk.

At the opposite end, pest attack during storage (A14) obtained the highest TOPSIS score of 0.8214 and ranked first, indicating that it was the least critical or most favourable constraint among the alternatives. Only 16.75% of farmers reported storage pest attack, further supporting its relatively lower priority compared with the other constraints.

The results also demonstrate that frequency alone cannot adequately determine the priority of agricultural constraints. For example, several constraints with relatively high frequencies did not necessarily obtain the lowest TOPSIS scores because the final ranking incorporates severity, occurrence, detection and environmental impact simultaneously. This demonstrates the usefulness of the Fuzzy-AHP–TOPSIS approach for complex agricultural decision-making where multiple and sometimes conflicting criteria must be considered.

The block-wise comparison further confirms that constraint intensity is spatially heterogeneous across the 16 surveyed blocks. Differences in irrigation availability, input accessibility, climatic exposure, farmer training, transportation, market access and storage infrastructure influence farmers' perceptions of individual constraints. Consequently, interventions should combine state- or district-level priorities with block-specific action plans.

Based on the findings, the following priorities are recommended:

1. Ensure timely availability of certified/ high-quality potato seed at affordable

prices, particularly before the planting season.

2. Strengthen seed distribution networks and institutional support to reduce farmers' dependence on costly or uncertain seed sources.
3. Improve irrigation infrastructure and water-management practices in blocks vulnerable to rainfall variability.
4. Strengthen market linkages, price information and collective marketing mechanisms to reduce the adverse effects of peak-season price fluctuations.
5. Improve access to farmer training and extension services, particularly concerning integrated pest management, nutrient management and climate-resilient production practices.
6. Expand and modernise cold-storage facilities while ensuring that storage services remain economically accessible to small and marginal farmers.
7. Improve rural transport and post-harvest logistics to reduce marketing delays and physical losses.
8. Promote block-specific interventions based on the local severity and occurrence profiles rather than applying identical solutions across all potato-growing areas.

In conclusion, the study establishes that the major challenge in the potato production system of the surveyed districts is not a single isolated problem but an interconnected set of input, climatic, economic, infrastructural and post-harvest constraints. Among these, affordable access to quality seed deserves the highest policy attention. The Fuzzy-AHP–TOPSIS framework provides a transparent and reproducible mechanism for converting farmers' perceptions into a structured priority order and can therefore support policymakers, extension agencies and other stakeholders in allocating scarce resources towards the most critical constraints. The incorporation of block-wise variation further enhances the practical value of the framework by enabling location-specific and priority-based strategies for sustainable potato production and storage in West Bengal.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

ETHICAL STATEMENT

This article does not contain any studies with animals. Responses received from human participants on purely voluntary basis during the survey.

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