



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
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NAAS Rating (2026): 5.20
www.agronomyjournals.com
2026; SP-9(4): 117-129
Received: 16-01-2026
Accepted: 19-02-2026

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Assessing risks in pigeon pea crop production for designing mitigation strategies: An FMEA approach

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DOI: <https://www.doi.org/10.33545/2618060X.2026.v9.i4Sb.5372>

Abstract

Pigeon pea farming in the rainfed agro-ecosystems of Southern Odisha is highly susceptible to climate fluctuations, especially unpredictable rainfall, droughts, and persistent cloud cover during key growth phases. This research combines long-term climate data, farmer insights, Failure Mode and Effects Analysis (FMEA), and Machine Learning (ML) to evaluate risks and identify mitigation options. Rainfall data (1994-2023) showed concentrated monsoon rainfall, with frequent rains over 200 mm from July to September, aligning with flowering and pod formation. Satellite data indicated over 80% cloudy days during this period, diminishing solar radiation and impacting yields. Farmers reported yield reductions of 10% to 50%, with Rayagada experiencing greater vulnerability. FMEA pinpointed major risks such as unfilled pods, pests, moisture stress, and late sowing, linked to rainfall variability and cloudiness. The ML model achieved high accuracy ($R^2=0.982$, RMSE=11.41 kg/ha), effectively predicting site-specific yield changes. Simulating a 15-day shorter crop cycle revealed that medium-duration varieties could sustain or boost yields, unlike traditional types which declined. Implementing seedling transplanting alongside ML-based yield prediction offers a promising method to reduce climate risks and improve resilience in rainfed pigeon pea systems. These insights support proactive, localized strategies from optimized sowing times to pest management with bio-inputs that promote climate-smart pigeon pea cultivation. By integrating empirical risk analysis with advanced predictive tools, this FMEA-ML framework provides a scalable model to protect smallholder farmers' yields amid growing climate challenges, fostering sustainable agriculture across rainfed regions in South Asia.

Keywords: Pigeon pea cultivation, FMEA, cloud cover, machine learning, yield prediction

1. Introduction

Pigeonpea (*Cajanus cajan* (L.) Millsp.) is a crucial grain legume widely grown in tropical and subtropical regions, especially in South Asia, where it provides an essential source of dietary protein and nutritional security (Saxena *et al.*, 2010; Varshney *et al.*, 2017) [33, 39]. In India, pigeonpea plays a vital role in rainfed agriculture and is well integrated into various cropping systems, such as intercropping and mixed cropping (Sawargaonkar *et al.*, 2025; Sawargaonkar *et al.*, 2026) [11, 12], due to its drought tolerance and ability to enrich soil through biological nitrogen fixation (Ali & Kumar, 2005) [1]. Despite its significance, pigeonpea yields remain relatively low compared to its potential. In Odisha, the crop is grown on over 1.33 lakh hectares, producing 1.39 lakh tonnes with an average yield of 1.04 t ha⁻¹ during 2021-22 (E&S Division, DA&FW). This is below the achievable yield of approximately 1.08 t ha⁻¹ (DES, Ministry of Agriculture & Farmers Welfare, Government of India), indicating a persistent yield gap that requires better management and risk mitigation strategies. Several biophysical and socio-economic factors contribute to this gap (Sawargaonkar *et al.*, 2024; Kumar *et al.*, 2024) [10, 29]. These include irregular rainfall patterns affecting crop establishment and growth, improper farming practices, a lack of region-specific high-yielding, climate-resilient varieties, low seed replacement rates (around 7%), and limited access to quality seeds and timely inputs (Rao *et al.*, 2015; Birthal *et al.*, 2014) [30, 4]. Additionally, waterlogging during the monsoon season hampers root aeration, nutrient uptake

(Pasumarthi *et al.*, 2024) ^[28-29], and nodulation, while increasing susceptibility to diseases, ultimately reducing plant survival and yields (Choudhary *et al.*, 2011) ^[6]. Since pigeonpea is primarily a Kharif crop, its productivity heavily depends on plant survival under multiple biotic and abiotic stresses throughout its growing cycle. Therefore, enhancing pigeonpea productivity is essential for increasing farmers' income, ensuring livelihoods, and strengthening food and nutritional security. However, most current studies focus on isolated constraints rather than addressing the interconnected risks farmers face throughout the entire production cycle. In reality, farmers manage diverse risks simultaneously under uncertain climatic and resource conditions, where unexpected events can substantially impact productivity and income (Hardaker *et al.*, 2004) ^[13]. The efficiency of agricultural systems hinges on identifying and correcting process-level failures, which remains a significant challenge, especially under climate variability. In this context, risk assessment is a vital tool for better decision-making and promoting sustainable agricultural development (Hardaker *et al.*, 2004) ^[13]. Failure Mode and Effects Analysis (FMEA), commonly used in industry for quality control and risk assessment, provides a structured approach to identify potential failures, analyze their causes and effects, and prioritize mitigation strategies (Stamatis, 2003) ^[36]. Applying this method in agriculture enables a comprehensive evaluation of risks across the crop production the process helps identify critical risk factors that impact farm performance. As a result, this study uses the FMEA framework on pigeonpea production systems to

- 1) Find key risk events and factors throughout the crop cycle,
- 2) Rank these risks by severity, likelihood, and detectability, and
- 3) Create specific strategies to reduce risks and boost productivity and resilience.

The findings are expected to help farmers and policymakers improve risk management, support sustainable pigeonpea farming, and enhance livelihood security.

Cloud cover is a vital agro-meteorological factor affecting pigeonpea (*Cajanus cajan* L.) growth and yield by regulating solar radiation, canopy temperature, and atmospheric humidity. It directly influences the availability of Photosynthetically Active Radiation (PAR), impacting biomass buildup and dry matter distribution. Extended cloudiness during vegetative growth can decrease photosynthesis efficiency and delay development, while moderate cloud cover may help reduce heat stress and lower evapotranspiration losses in rainfed systems. However, excessive cloud cover during reproductive stages, such as flowering and pod filling, can harm pollen viability, increase flower drop, and decrease pod production, ultimately lowering yield. Additionally, persistent cloudiness often elevates relative humidity, promoting disease incidence and further limiting productivity. Since pigeonpea yield is highly sensitive to climate variability under rainfed conditions, the interactions among radiation, temperature, and moisture regimes play a key role in yield fluctuations (Saxena *et al.*, 2010; Chauhan *et al.*, 2019) ^[33, 5]. Therefore, incorporating

cloud cover dynamics into yield-prediction frameworks is crucial to enhancing accuracy and climate resilience in pigeonpea farming.

Machine Learning (ML) and deep learning approaches, especially Convolutional Neural Networks (CNNs), are increasingly seen as effective alternatives or complements to traditional process-based crop simulation models like DSSAT and APSIM. While DSSAT/APSIM depend on predefined physiological relationships and require extensive calibration using genotype, soil, and management data, ML models are data-driven and can capture complex, non-linear interactions among weather variables, soil properties, and crop responses (Jones *et al.*, 2003; Holzworth *et al.*, 2014) ^[20, 16]. Recent research shows that ML and deep learning models, including CNNs and LSTM networks, greatly improve yield prediction accuracy by utilizing large datasets such as remote sensing imagery and meteorological time-series data (Hernández *et al.*, 2025) ^[15]. CNN models, in particular, have proven to perform better than traditional statistical and simulation models by efficiently extracting spatial and temporal features and reducing prediction errors (Srivastava *et al.*, 2021). Moreover, AI-based models have achieved high predictive performance ($R^2 > 0.85$) and significant reductions in error compared to conventional approaches (Hernández *et al.*, 2025) ^[15]. Unlike DSSAT/APSIM, ML models require fewer explicit assumptions and can be dynamically updated with real-time data, making them highly scalable across diverse agro-ecological regions. For farmers, this allows timely decisions on sowing windows, irrigation schedules, and risk management under uncertain climatic conditions. For researchers, ML models offer a powerful tool for identifying key yield-driving factors and complementing process-based simulations. Therefore, integrating ML methods with traditional crop models provides a strong path toward data-driven, climate-resilient agriculture in pigeonpea-based systems.

This study is essential as it integrates cloud cover dynamics, CNN-based yield prediction, and FMEA risk assessment to address interconnected constraints in pigeonpea production. By combining predictive accuracy with systematic risk prioritization, it offers a holistic, scalable framework for improving yield forecasting and resilience under climate variability. The approach supports informed decision-making for farmers and researchers, enabling targeted interventions, reducing yield gaps, and promoting sustainable, climate-smart pigeonpea cultivation.

2. Material and methods

2.1 Study area

The current study was carried out in two districts, Gajapati and Rayagada, in the state of Odisha, India. The study used proportionate random sampling to gather information on the agronomy of pigeonpea and employed focus group discussions to assess risks in pigeonpea production and to gather insights into challenges and local knowledge systems used to address them. The research was conducted across 15 villages in Rayagada district and 16 villages in Gajapati district (Table 1).

Table 1: Sampling plan

Rayagada Gajapati					
Name of GP	Name of Village	No of samples	Name of GP	Name of Village	No of samples
Chatikona	Chatikona	1	K Sitapur	Champeinguda	7
	New Chatikona	6		Sri Bishnupur	10
Daliakunji	Daliakunji	11	Kharada	Tadava	5
Durgi	Durgi	2	Namnaguda	Amburudi	5
	Khalapai	2		Adha Singh	7
	kurampadar	3		Baruda	7

H. Muniguda	H. Muniguda	10		Parthada	5
Jagdalpur	Bhuragaon	7	Ragedi	Sanmarul	2
	Birli	7	Ragidi	Ragedi	14
Kumardhamanui	Kumardhamanui	7		Tuburda	5
Kumudabali	Khajuripadar	7	Tarava	Buruding	9
	Ladipanga	5		Samaghaita	2
	Singari	18		Tarava	5
Patraguda	Bhursikhamar	7	Ukhara	Lakisar	4
Thuapadi	Thuapadi	9		Sratal	13
				Ukhara	9
Total		102			109

2.2 Rainfall pattern

Analyzing rainfall data and its patterns, such as floods, heavy rainfall, and droughts, helps understand extreme weather events and optimize agricultural practices for better crop production and revenue. The rainfall data from 1994 to 2024 (30 years) was obtained from four weather stations located at project sites and further analyzed. Coefficient of variation, standard deviation, and averages were calculated to check the consistency of rainfall during the crop season.

2.3 Failure mode and effect analysis

The FMEA method can be applied in project risk management because of its simplicity, familiar format, and comprehensive structure. In traditional FMEA, the ranking of critical failure modes is done through Risk Priority Numbers (RPN), which are calculated by evaluating factors such as occurrence probability (O), severity (S), and detection (D) for each failure mode. A risk priority number is obtained by multiplying the severity (S), occurrence (O), and detection (D) ratings. A high score indicates a high risk of non-delivery and should be prioritized for developing an appropriate mitigation plan. The individual scores help identify where mitigation efforts should be concentrated. The highest scores should be addressed as a high priority, while the lowest scores may not require mitigation action signed.

$$RPN_n = S_n * O_n * D_n$$

Specifically,

- S_n refers to the severity of Item “n”; How serious is the effect of the failure? (Scale 1-10)
- O_n is the occurrence of Item “n”; How likely is it to happen? (Scale 1-10)
- D_n refers to the detection of Item “n”. How likely is it that the failure will be detected before it causes harm? (Scale 1-10)

Using the formula, the highest theoretically possible RPN value is 1000 ($10 \times 10 \times 10$) and the lowest possible value is 1. There is no best practice or rule of thumb for setting the RPN threshold; organizations use values between 40 and 150, depending on the maturity of their process or product/process requirements, with the most frequently used value around 100 (Mascia *et al.*, 2020) [40].

2.4 Cloud cover analysis

Cloud cover is a critical agro-meteorological variable influencing pigeonpea productivity through its effects on solar radiation, temperature regime, and atmospheric humidity [40]. It directly regulates photosynthetic activity, crop phenology, and reproductive success, while indirectly affecting disease dynamics and soil moisture balance. Given its stage-specific impact—particularly during flowering and pod development—cloud cover plays an important role in determining yield variability under rainfed conditions

The Moderate Resolution Imaging Spectroradiometer (MODIS), onboard NASA’s Terra and Aqua satellites, captures data across multiple spectral bands that are essential for detecting and analyzing cloud cover in daily satellite imagery. Key bands used for cloud identification include those in the visible spectrum (e.g., Band 1: 620-670 nm), near-infrared (e.g., Band 2: 841-876 nm), shortwave infrared (e.g., Band 6: 1628-1652 nm), and thermal infrared (e.g., Band 31: 10.78-11.28 μ m). These bands are used in various cloud detection algorithms, including thresholding, reflectance-ratio tests, and brightness-temperature assessments, to differentiate clouds from clear-sky pixels and to determine cloud properties such as phase, temperature, and optical thickness. In the present study, MODIS daily surface reflectance data (MODIS/061/MOD09GA) were utilized to extract cloud cover information at the village level. Village boundary shapefiles for 16 villages in Gajapati and 15 in Rayagada districts of Odisha, India, were overlaid on MODIS imagery in the Google Earth Engine (GEE) platform. Using this cloud detection approach, the total number of cloudy days for each village was quantified over a two-year period from 2023 to 2024, providing valuable insights into local-scale cloud dynamics and atmospheric conditions.

2.5 Yield prediction using CNN integrated with DSSAT outputs

In this study, pigeon pea yield prediction was carried out using a Convolutional Neural Network (CNN) model. The dataset was collected from the Bissam Cuttack region in the Rayagada district and included simulated yield values (HWAM) generated using the DSSAT crop model, along with relevant agro-climatic and soil parameters.

2.6 The model incorporated the following features:

- Climate variables: TMAXA, TMINA, SRADA, DAYLA, CO₂A
- Water balance variables: PRCM, ETCM, EPCM, ESCM, ROCM, DRCM, SWXM
- Daily variables: PRCP, ETCP, ESCP
- Soil and nutrient variables: Nitrogen, organic matter (OM), ONAM, OCTAM
- Crop parameters: PDAT, NDCH, HWAM

TMAXA: Average Maximum Temperature
 TMINA: Average Minimum Temperature
 SRADA: Average Solar Radiation
 DAYLA: Average Day Length
 CO₂A: Average CO₂ Concentration
 PRCP: Daily Precipitation
 ETCP: Daily Evapotranspiration
 ESCP: Daily Soil Evaporation
 Nitrogen (Kg/ha): Fertilizer application rate
 OM (t/ha): Organic Matter in tons per hectare.
 NDCH: Number of Days to Crop Harvest

HWAM: Yield (Harvested Weight per unit area in kg/ha)
 PDAT: Planting Date
 PRCM: Cumulative Precipitation
 ETCM: Cumulative Evapotranspiration
 EPCM: Cumulative Potential Evapotranspiration
 ESCM: Cumulative Soil evaporation
 ROCM: Runoff
 DRCM: Drainage
 SWXM: Maximum Soil Water
 ONAM: Amount of Organic Nitrogen Applied
 OCTAM: Amount of Organic Carbon Applied

2.7 The dataset included the following input variables

The raw data was first cleaned by removing non-numeric characters and dropping missing values. The target variable was HWAM (harvestable yield), and all other columns were used as input features. The dataset was split into training, validation, and testing sets. Feature scaling was applied using the StandardScaler to normalize the data. The CNN model was built with two 1D convolutional layers, a global average pooling layer, and dense

layers, followed by a dropout layer to prevent over fitting. The model was trained using the Adam optimizer and Mean Squared Error (MSE) as the loss function, with the R^2 metric used to evaluate performance. Early stopping was used to avoid overtraining. Finally, the trained model was evaluated on the test dataset, and the results were visualized using scatter plots of actual versus predicted yields.

3. Results and discussion

3.1 Socio-demographic features

3.1.1 Demographic features

Pigeonpea farmers are typically middle-aged, with an average age of around 43 years (Gajapati), while Rayagada farmers (47.5) are older and have a moderate level of formal education (primarily primary education). Their family sizes average about five members, and the male-to-female ratio is nearly 1:1. The farmers have over two decades of experience in agriculture, while only a few farmers have just three years of experience in cultivating pigeonpea. (Table 2).

Table 2: Demographic features of respondents

Attributes	Gajapati	Rayagada
Size of the family	5.5	5.0
Male	2.8	2.6
Female	2.7	2.4
No of adults engaged in agriculture (own farm)	2.3	2.7
Age of the HH	43.5	47.5
Education levels of HH	4.7	4.8
Total farming experience	21.1	23.1
Pigeonpea farming experience	3.6	3.2

3.1.2 Farmers classification

These farmers were grouped into four categories based on their landholdings: marginal (up to 1.00 ha), small (1.01 ha to 2.00 ha), medium (2.01 ha to 4.00 ha), and large (more than 4.00 ha). The results showed that about 45% of the sample farmers (Figure 1a)

were small, followed by marginal (38%), medium (16%), and large (1%) farmers in the Gajapati sample villages. The distribution in Rayagada (Figure 1b) is similar to that in Gajapati, but the proportion of large farmers (11%) is higher than in the Gajapati sample villages.

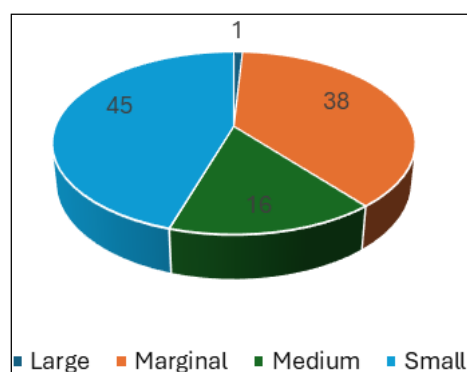


Fig 1A: Farmers classification- GAJAPATI

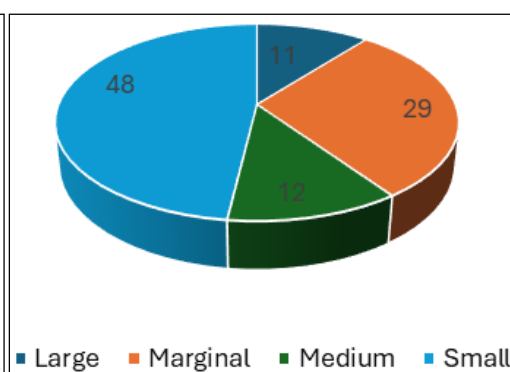


Fig 1B: Farmers classification- RAYAGADA

3.1.3 Landholdings and extent of tenancy

The details of landholdings and tenancy extent district-wise are provided in Table 3. The average total landholding per household in the Gajapati sample was estimated at 1.38 hectares, with 0.15 ha under partial irrigation, 0.22 ha under irrigation, and an

additional 1 ha under rainfed cultivation (Table 3). In Rayagada district, the average landholding size is 1.83 hectares, with rainfed holdings making up 64% of total holdings. Leased-in land is significant in Rayagada but non-existent in Gajapati.

Table 3: Size of land holding and extent of tenancy

Land Type	Ownership	Gajapati	Rayagada
Rainfed Land	Own land	1.00	1.17
	Leased/ shared in land		0.08
	Leased/shared out land		
Partially Irrigated	Own land	0.15	0.14
	Leased/ shared in land		0.29
	Leased/shared out land		
Irrigated	Own land	0.22	0.08
	Leased/ shared in land		
	Leased/shared out land		
Permanent fallow	Own land		0.07
	Leased/ shared in land		
	Leased/shared out land		
Total	Own land	1.38	1.46
	Leased/ shared in land		0.38
	Leased/shared out land		0.02

3.2 Pigeonpea crop management and economics

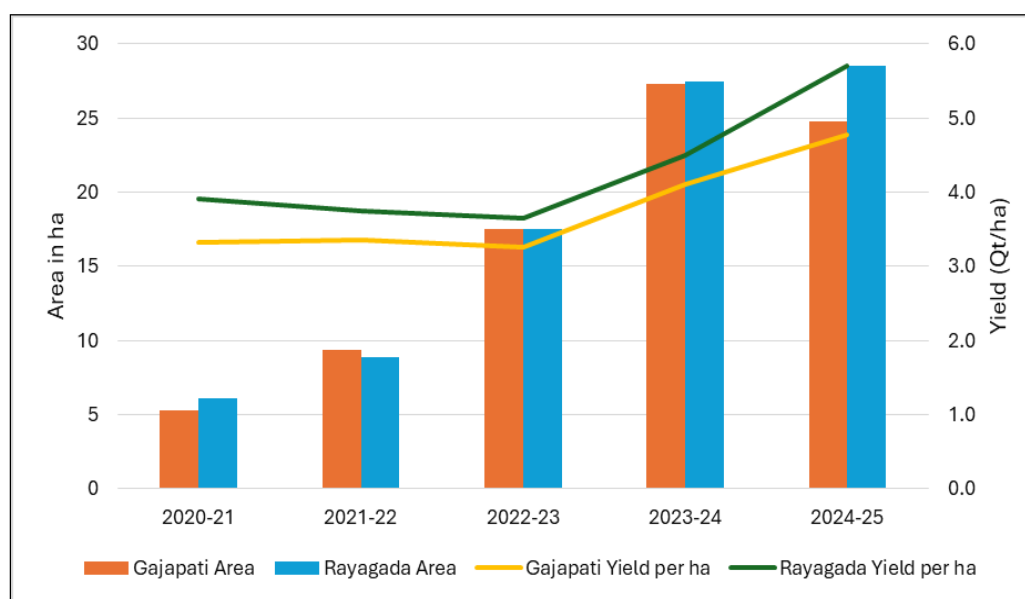
3.2.1 Trends in pigeonpea area and productivity

The area under pigeonpea cultivation in the study region remains extremely limited despite recent expansion. In Gajapati district, the cultivated area increased from 5.29 ha in 2020-21 to 24.73 ha in 2024-25, while in Rayagada it expanded from 6.10 ha to 28.50 ha over the same period (Figure 2), representing a 3.67-fold increase. However, it is important to note that this growth originates from a very small baseline area, indicating that pigeonpea still occupies only a marginal share of the total cropped area in the study region.

The observed increase reflects a gradual shift towards promoting pigeonpea cultivation in rainfed upland ecosystems, driven by its potential to enhance food and nutritional security and farmer livelihoods. Given its perennial growth habit and deep root system, pigeonpea is particularly suited to upland conditions, where it contributes to soil conservation by reducing runoff and

erosion, especially during the early stages of crop establishment. Despite the positive trend, the overall adoption rate remains limited, suggesting significant scope for expansion through targeted interventions, such as improved varieties, climate-resilient practices, and enhanced extension support. The corresponding trends in productivity from 2020-21 to 2024-25 are presented in Figure 2.

The average productivity in the study region in 2024-25 is 4.8 qt/ha in Gajapati and 5.7 qt/ha in Rayagada, representing a significant increase of over 40% from 2020 to 2024. While productivity levels have fluctuated slightly, they have remained largely flat in both regions. For further adoption, it is crucial to implement measures that enhance productivity in pigeonpea cultivation. These include varietal improvement, introducing climate-resilient technologies, adopting improved cultural and management practices, implementing effective disease control, and ensuring efficient water use management

**Fig 2:** Trends in Pigeonpea area and productivity (2020-21 to 2024-25)

3.2.2 Fertilizer use pattern

For pigeonpea cultivation in Odisha, a common NPK recommendation is 20:40:20 kg ha⁻¹, comprising 20 kg of Nitrogen (N), 40 kg of Phosphorus (P₂O₅), and 20 kg of Potassium (K₂O) per hectare. Table 4 shows the existing fertilizer use pattern in selected districts. The nitrogen application at Rayagada is significantly higher than the recommended level, three times

higher, while at Gajapati, the applied rate is nearly in line with the recommendation. In Rayagada, the phosphorus applied (37.6 kg ha⁻¹) is below the recommended 40 kg ha⁻¹; however, in Gajapati, phosphorus application is about 65% lower than the guideline. The farmers did not use any potassium-containing fertilizers, which may have contributed to the low productivity.

Table 4: Fertilizer use pattern in study villages

District	Application time	Dosage (kg ha ⁻¹)	
		Nitrogen	Phosphorous
Rayagada	Basal	34.4	16.8
	30 days after sowing (DAS)	30.2	20.8
Gajapati	Basal	0.0	0.0
	30 (DAS)	25.4	14.2

3.2.3 Pest incidence in pigeonpea farming (Only rayagada)

The frequency of pesticide application was determined based on farmers' reports of pest occurrence. Pigeonpea cultivation in the study area is greatly impacted by insect pests, with pod borers being the most damaging (Table 5). The main species identified include *Helicoverpa armigera* (gram pod borer) and *Melanagromyza obtusa* (pod fly). Analysis of spray patterns showed that about 37% of applications during the first pest outbreak and 50% during the second targeted pod borer infestations.

These pests cause significant yield reductions by damaging vital reproductive structures such as buds, flowers, and developing

pods, which directly lowers grain formation and productivity. The heavy dependence on pesticide sprays in Rayagada highlights the severity of pest pressure, while in Gajapati, the lack of systematic pest management practices further increases the risk of yield losses.

These results emphasize the importance of adopting Integrated Pest Management (IPM) strategies, including regular monitoring, use of resistant varieties, biological control methods, and application of chemicals based on need, to effectively control pest outbreaks and enhance pigeonpea production under current site conditions.

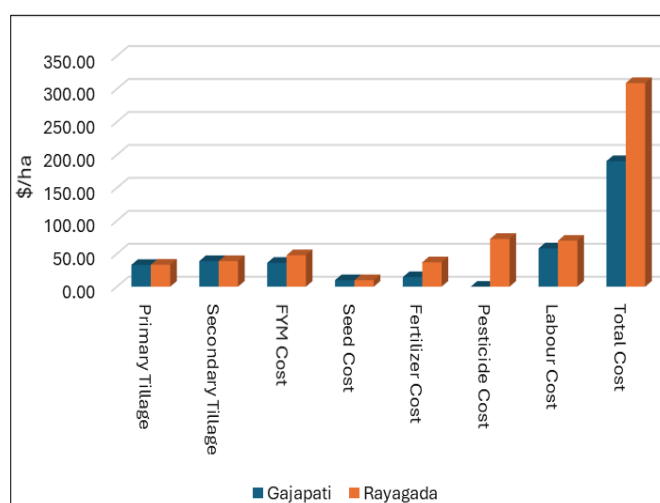
Table 5: Frequency of pesticide application

Pests	% sprays	
	Ist Spray	2nd Spray
Pod borer	37	50
Pod fly	15	2
Sterility mosaic virus	9	0
Leaf minors	6	3
Pod suckers	3	0
No Pesticides	30	45

3.2.4 Cost of cultivation

The cost of pigeonpea cultivation is shown in Figure 3. On average, the per-hectare cost was estimated at \$190 in Gajapati and \$309 in Rayagada. The major costs in pigeonpea cultivation were human labor (30%), secondary tillage (20%), and FYM (19%). Farmers in Gajapati do not implement any pest control measures, so there are no pesticide costs.

In Rayagada, both pesticides and human labor constitute a major share (23%). However, when combined, primary and secondary tillage together make land preparation the largest component, accounting for 33% of the total cultivation costs in Gajapati. All operations are performed by family labor, saving farmers in both districts \$. 59 to 71.

**Fig 3:** Cost of cultivation of pigeonpea

3.2.5 Economic returns of pigeonpea cultivation

Per-hectare profitability of pigeonpea cultivation is shown in Table 6. The average yield was 4.78 q ha⁻¹ in Gajapati and 5.69 q ha⁻¹ in Rayagada. The corresponding average market prices were \$78 per quintal in Gajapati and \$90 per quintal in Rayagada, resulting in gross returns of \$371 ha⁻¹ and \$512 ha⁻¹, respectively.

Net returns were estimated at \$180 ha⁻¹ in Gajapati and \$203 ha⁻¹ in Rayagada.

The Benefit-Cost Ratio (BCR) was higher in Gajapati (1.9) than in Rayagada (1.7), despite lower yields and prices. The relatively lower BCR in Rayagada is mainly due to higher cultivation costs, especially pesticide expenses, which were not incurred in

Gajapati. Other contributing factors include higher nitrogen application, increased use of Farmyard Manure (FYM), and higher labor costs.

These findings suggest that increased input use does not always lead to proportionate economic gains under rainfed conditions.

Improving input efficiency through balanced nutrient application, targeted pest management, and optimized labor use can enhance profitability. Implementing suitable management practices could significantly boost returns from pigeonpea cultivation in the study area.

Table 6: Economics of pigeonpea cultivation

Parameters	Gajapati	Rayagada
Yield (Qt/ha)	4.78	5.69
Price (\$/qt)	78	90
Gross Returns (\$/ha)	371	512
COC (\$/ha)	190	309
Net Returns (\$/ha)	180	203
BCR	1.9	1.7

3.3 Risks in pigeonpea production

Pigeonpea is highly sensitive to low levels of solar radiation during pod development. Cloudy weather, persistent fog, and low temperatures during the critical flowering and podding stages negatively impact physiological processes, leading to poor pod formation and ultimately reduced yields. According to Patil *et al.* (2018), rainfall in August had the most significant impact on seed yield across all varieties, followed by July and September. Therefore, understanding the rainfall pattern and the months with heavy rainfall is essential for managing pigeonpea crop production.

3.3.1 Rainfall-farmers perception

Climate change and increasing climate variability greatly limit farmers' ability to make informed, strategic decisions throughout the agricultural cycle, including varietal selection, sowing time, input management, pest control, and harvesting. This issue is especially critical in rainfed systems of India, where crop productivity heavily depends on monsoon patterns and intra-seasonal rainfall variability (ICRISAT, 2012; Morton, 2007) [7]. Farmers' perceptions of climatic risks are therefore vital in shaping adaptive strategies and farm-level decision-making (Below *et al.*, 2012) [3]. The current study examined climate-related risks in pigeonpea cultivation based on farmers' perceptions of the frequency and impact of such events over the past five years. Yield losses were measured as a percentage (0-100%), reflecting the perceived severity of climatic stressors in the field.

In Gajapati district, most farmers identified prolonged cloudy periods (79% of respondents) and early monsoon withdrawal (69%) as the top constraints affecting pigeonpea cultivation (Figure 8). The average perceived yield loss due to heavy rainfall was around 38%, followed by early rainfall cessation (37%) and

late monsoon onset (37%). Overall, perceived yield losses from extreme rainfall events ranged from 10% to 50% (Figure 4).

In Rayagada district, late monsoon onset was the main climatic risk, reported by 94% of farmers (Figure 5), followed by prolonged overcast weather (68%) and early monsoon withdrawal (60%). The average perceived yield loss due to heavy rainfall was higher than in Gajapati, at 44% (Figure 5). Other factors included extended cloudy periods (39%), delayed monsoon start (35%), and prolonged dry spells during the cropping season (35%).

Across both districts, farmer perceptions consistently highlight the critical influence of cloud cover, rainfall variability, and monsoon timing on pigeonpea productivity. These findings are supported by physiological studies indicating that reduced solar radiation and excess moisture during flowering and pod development adversely affect yield formation in legumes (Craufurd *et al.*, 2003; Indian Institute of Pulses Research, 2018) [8]. Similarly, variability in rainfall timing and intensity has been widely reported to influence crop yields in rainfed agricultural systems (Ray *et al.*, 2015; Lobell *et al.*, 2011) [31, 25].

The relatively higher perceived yield losses in Rayagada suggest greater climatic vulnerability, likely due to delayed monsoon onset and increased exposure to rainfall variability during critical growth stages. The strong alignment between farmer perceptions and scientific evidence reinforces the reliability of local knowledge in identifying key production constraints.

Overall, these results emphasize the need for location-specific adaptation strategies, including climate-resilient varieties, improved agronomic practices, and weather-based decision support systems. Addressing challenges associated with prolonged cloudy periods and rainfall irregularities is essential to stabilize yields and enhance productivity in rainfed pigeonpea systems (Saxena *et al.*, 2010; Varshney *et al.*, 2017) [33, 39].

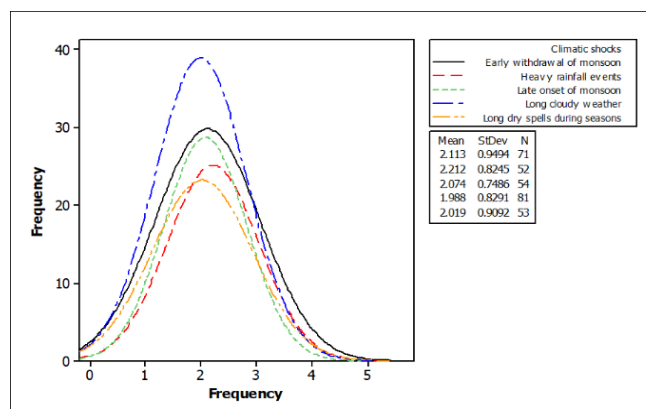


Fig 4: Perceived occurrence of climate events

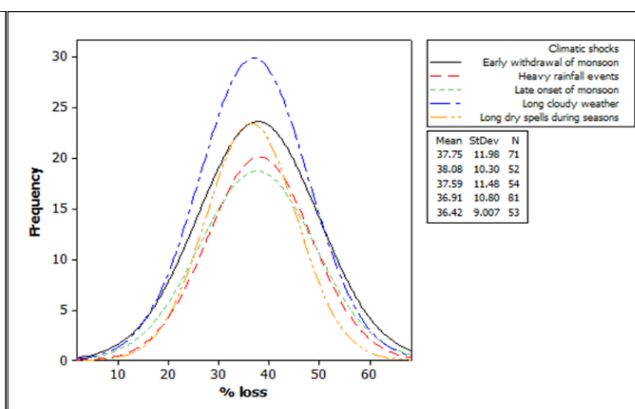


Fig 5: Perceived losses due to climate events

3.3.2 Risk prioritization and mitigation strategies (FMEA-based analysis)

Figure 6 presents farmers' perceptions of 17 risk events associated with pigeonpea cultivation across the selected villages. Using Failure Mode and Effects Analysis (FMEA), these risks were quantified and prioritized based on their Risk Priority Number (RPN) (Table 8), enabling identification of the most critical constraints affecting productivity at the study sites.

In Gajapati district, the major risks with RPN values exceeding 100 included low grain price at harvest, unfilled pods, Sterility Mosaic Virus (SMV) incidence, low yield, pod borer damage, moisture stress during critical growth stages, and delays in sowing due to late monsoon onset. These risks reflect a combination of market-related, climatic, and biotic stresses influencing production.

In contrast, Rayagada farmers reported a broader range of high-priority risks, including weed infestation, low yield, heavy rainfall immediately after sowing, SMV incidence, unfilled pods, poor access to quality seeds, low plant survivability, premature flower drop due to prolonged cloud cover, heavy rainfall during harvest, uneven grain size, pod borer damage, stunted crop growth, and moisture stress during critical stages. The greater diversity of risks in Rayagada suggests higher system vulnerability, particularly to climatic variability and input-related constraints. Across both districts, several common risks, such as unfilled pods, pest incidence, and moisture stress, are closely linked to rainfall irregularities and persistent cloud cover, reinforcing the interconnected nature of climatic and biological stresses. These findings highlight the need for targeted, site-specific interventions to address the most critical constraints.

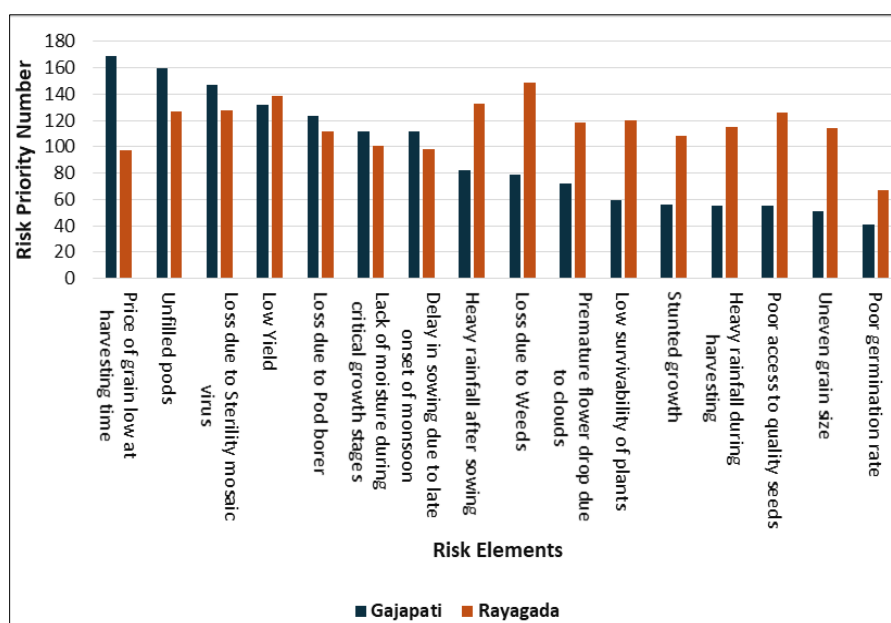


Fig 6: Farmers perceptions on risk elements in pigeonpea production-FMEA method

Based on the prioritized risks, the following management strategies are recommended

➤ Price risk (low market price)

- Strengthening market linkages through Farmer Producer Organizations (FPOs)
- Promoting collective marketing and aggregation to improve bargaining power

➤ Unfilled pods

- Selection of varieties with compact and synchronous pod setting
- Adoption of early- or medium-duration varieties suited to rainfall patterns
- Effective management of pod borer and pod fly infestations
- Promotion of pest-tolerant varieties
- Correction of nutrient deficiencies, particularly boron and phosphorus
- Application of basal fertilizers (DAP or SSP), especially in areas where nutrient application is currently inadequate

➤ Sterility Mosaic Virus (SMV)

- Adoption of SMV-resistant varieties
- Control of the eriophyid mite vector
- Farmer awareness on rouging of infected plants and field sanitation

- Seed treatment with Rhizobium, *Trichoderma*, and phosphorus-solubilizing bacteria (PSB)

➤ Weed infestation

- Proper land preparation with 2-3 rounds of ploughing followed by harrowing to suppress weeds
- Promotion of mechanical weeding (e.g., rotary weeders)
- Use of allelopathic plants to reduce weed pressure and enhance additional income opportunities

3.3.3 Rainfall pattern and intensity

Daily rainfall data from 1994 to 2023 were collected and analyzed for four meteorological locations, Gumma and Kashinagar (Gajapati district) is presented in Figure 7 and Bissam, Cuttack, and Muniguda (Rayagada district) are presented in Figure 8. The 30-year average annual rainfall was estimated at 1329 mm in Bissam Cuttack, 1382 mm in Muniguda, 1379 mm in Gumma, and 1284 mm in Kashinagar, indicating a relatively high rainfall regime across the study sites.

The Southwest monsoon (June to September) contributed a major share of annual rainfall, accounting for 75% in Bissam Cuttack, 79% in Muniguda, 63% in Gumma, and 66% in Kashinagar. This concentration of rainfall during the monsoon season highlights the dependence of crop production on monsoonal precipitation patterns in the region.

Pigeonpea, a long-duration crop, is typically sown during the first and second fortnights of July and is predominantly cultivated under rainfed conditions on flatbeds in the study area. However, rainfall exceeding 200 mm per month during the critical period from July to September (Figures 7 and 8) poses a significant risk to crop performance. Excess moisture during this phase coincides with vegetative and early reproductive stages, leading to adverse effects on flowering, pollination, and pod development. Supporting this observation, Patil *et al.* (2018) reported that excessive rainfall and cloudy weather during the flowering stage (50-65 days after sowing) result in substantial yield losses in pigeonpea. Furthermore, statistical analysis revealed a relatively low Coefficient of Variation (CV) coupled with a high standard

deviation during the monsoon months, indicating that rainfall is consistently concentrated around high mean values. This suggests that monthly rainfall exceeding 200 mm is a recurring phenomenon during July-September over the past three decades (Figure 7 and 8).

Such rainfall patterns, combined with persistent cloud cover, create unfavorable conditions for pigeonpea productivity in the study region. These findings underscore the need for adopting climate-resilient varieties, improved drainage and field management practices, and weather-informed agronomic interventions to mitigate the adverse impacts of excess rainfall and ensure yield stability under rainfed conditions.

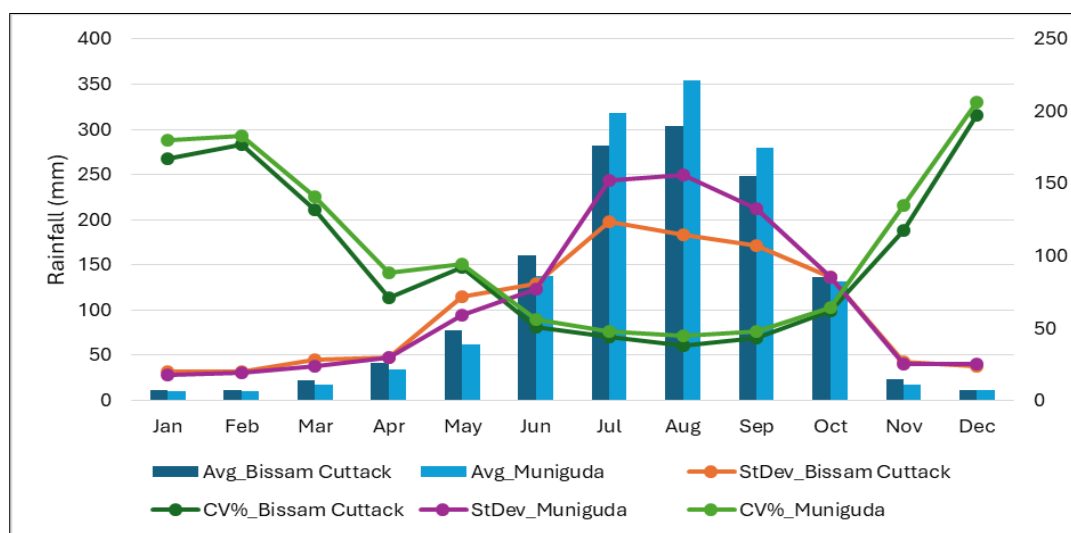


Fig 7: Rainfall pattern in Gajapati

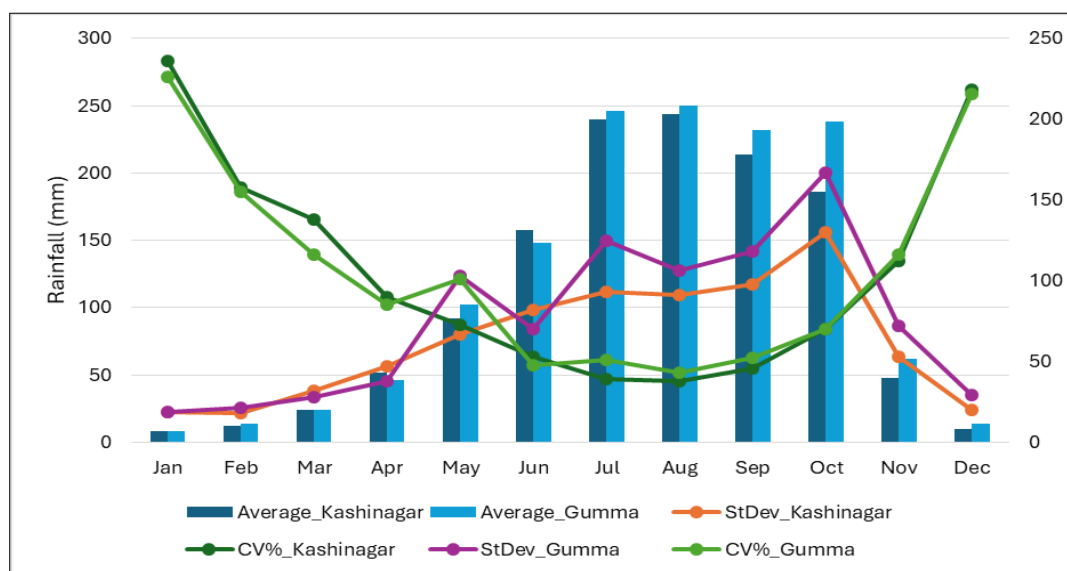


Fig 8: Rainfall pattern in Rayagada

3.3.4 Cloudy days

Analysis of daily satellite imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS) revealed a high prevalence of cloud cover during the monsoon season across the study sites. In Gajapati district, more than 80% of days between July and September were classified as cloudy during both 2023 and 2024 across all 17 study villages (Figure 9). A similar pattern was observed in Rayagada district, where MODIS analysis across 15 villages indicated that approximately 80% of days during the

same period were cloudy (Figure 10), corresponding to nearly 24-26 cloudy days per month.

This persistent cloud cover coincides with the critical growth stages of pigeonpea, particularly flowering and early pod development, when adequate solar radiation is essential for photosynthesis and reproductive success. Reduced solar radiation due to prolonged cloudiness limits assimilate production, leading to poor flower retention, reduced pod set, and ultimately lower yields.

These findings are consistent with previous studies indicating that cloudy weather, often accompanied by excessive rainfall during the flowering stage, significantly affects crop productivity by disrupting physiological processes (Craufurd *et al.*, 2003; Patil *et al.*, 2018)^[8]. The combined effect of high rainfall and prolonged cloud cover further exacerbates stress conditions in rainfed systems.

Overall, the results highlight that persistent cloud cover during the monsoon months is a critical climatic constraint in the study region. Addressing this challenge requires adopting climate-resilient varieties, improving crop management practices, and implementing weather-based advisory systems to mitigate the adverse effects on pigeonpea productivity.

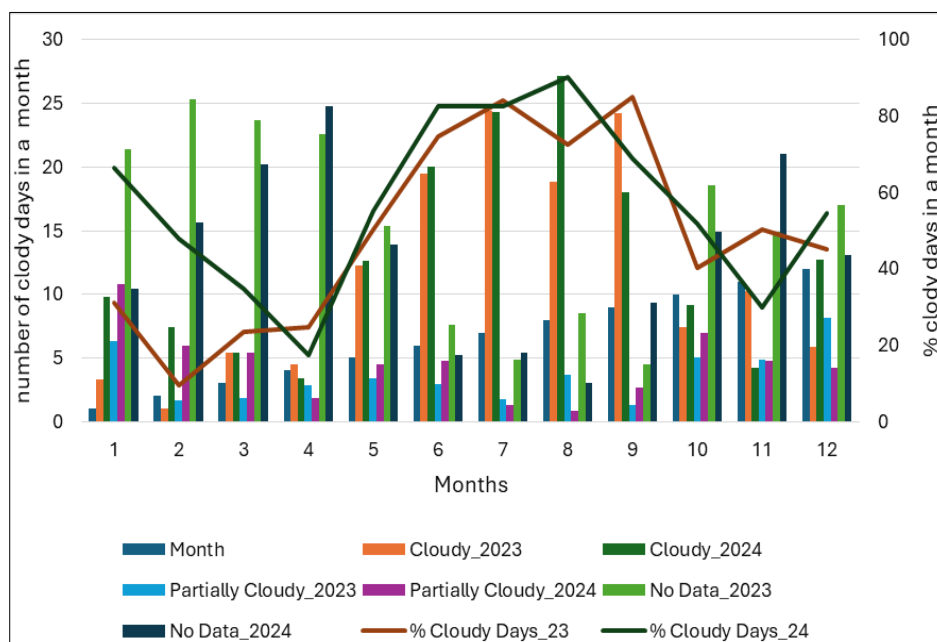


Fig 9: Month wise number and percentage of cloudy days -gajapati

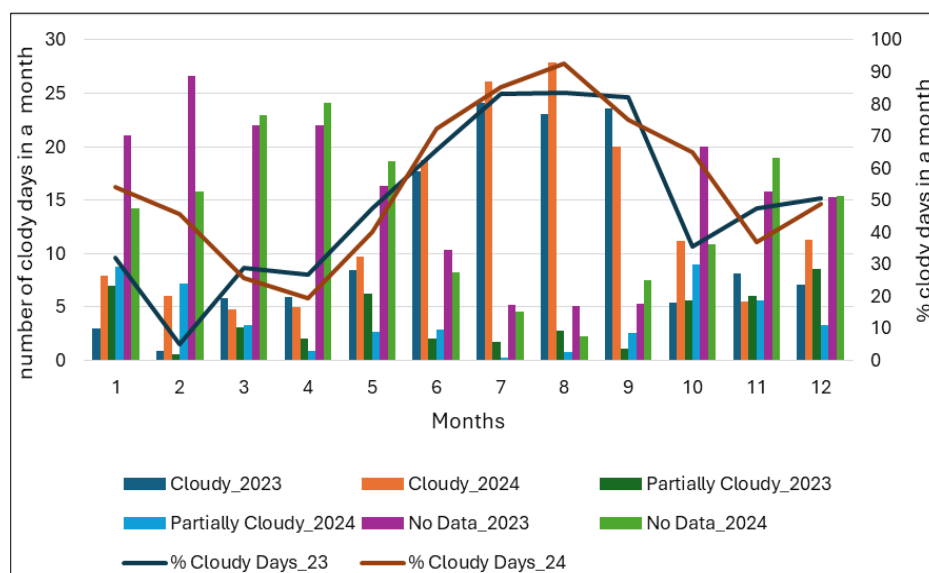


Fig 10: Month-wise number and percentage of cloudy days-Rayagada

3.4 Risk mitigation strategies

3.4.1 The Hybrid approach to pigeonpea crop yield prediction using process-based crop simulation models & AI/ML algorithms

The Machine Learning (ML) model demonstrated high predictive accuracy for pigeonpea yield under the rainfed agro-ecosystems of the study sites in Southern Odisha. The scatter plot of predicted versus observed yields showed a close alignment of data points along the 1:1 line, indicating strong agreement between model estimates and field observations under the prevailing environmental and management conditions.

The model achieved a coefficient of determination (R^2) of 0.982, indicating that 98.2% of the variability in observed yield was explained by the model (Figure 11). This high explanatory power suggests that the selected input variables-particularly site-specific weather parameters such as rainfall distribution and cloud cover, along with soil characteristics and crop management practices-effectively captured the drivers of yield variability across the study locations.

The Root Mean Square Error (RMSE) of 11.41 kg ha⁻¹ and Mean Absolute Error (MAE) of 8.11 kg ha⁻¹ further confirm the robustness of the model, reflecting low prediction error at the site

level. The relatively small difference between RMSE and MAE indicates a consistent error distribution with minimal influence of

extreme deviations, demonstrating model stability across seasons and locations within the study area.

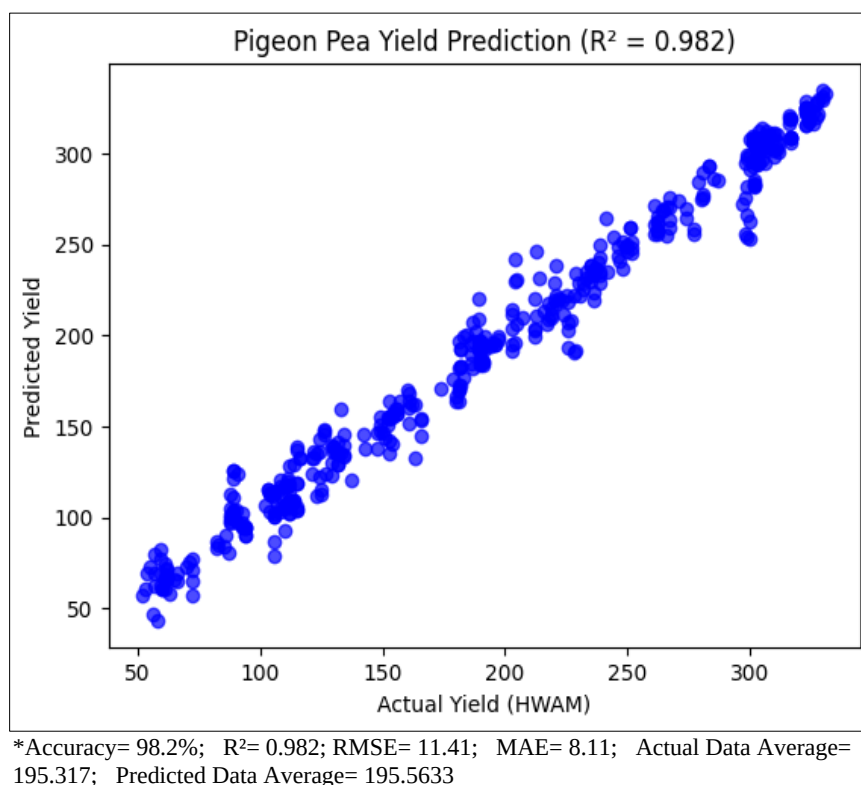


Fig 11: Yield prediction of pigeon pea using machine learning

Pigeonpea cultivation at the study sites is predominantly rainfed and highly sensitive to intra-seasonal rainfall variability, dry spells, and persistent cloud cover during reproductive stages. The strong predictive performance of the ML model indicates its ability to effectively capture these localized agro-meteorological influences. In particular, integrating rainfall patterns and cloud cover information appears to have significantly contributed to the accurate representation of yield variability under site-specific conditions.

In comparison, process-based models such as DSSAT and APSIM require detailed input data and extensive calibration to achieve comparable accuracy. Under the data-constrained conditions of the study sites, their application is often limited. The ML approach, by contrast, demonstrated high accuracy using available datasets, making it more practical and adaptable for operational use in these environments.

Site-Specific Implications for Risk Mitigation

The ML-based yield prediction framework provides a valuable tool for reducing production risk in the study area. Given the strong dependence of pigeonpea productivity on rainfall variability and cloud cover, the model enables early and reliable yield estimation, supporting timely and location-specific decision-making.

At the farm level, the model can facilitate

- Adjustment of sowing windows in response to anticipated rainfall patterns
- Selection of suitable crop varieties aligned with seasonal conditions

- Planning of contingency measures during expected dry spells or adverse weather events

At the local and administrative level, the model supports:

- Efficient planning of input distribution and resource allocation
- Improved estimation of production for local markets and procurement systems
- Reduction of uncertainty in rainfed agricultural production

Overall, the results demonstrate that ML-based approaches can serve as effective decision-support tools by linking climate variability with yield outcomes. Their integration into extension systems can enhance adaptive capacity, improve risk management, and contribute to more resilient pigeonpea production under site-specific rainfed conditions.

3.4.2 Crop Duration Adjustment as a Risk Mitigation Strategy

The yield under reduced crop duration (15 days) was predicted using machine learning (ML) techniques, revealing differential responses across genotypes and highlighting its importance as a climate risk mitigation strategy. The decline in yield observed in Maruti (−14.2%) indicates that medium-duration varieties are sensitive to shortened growth periods, as reproductive phases such as flowering and pod filling are constrained. In contrast, hybrids such as ICPH 2740 (+1.72%) and ICPH 3762 (+5.02%) maintained or improved yields (Figure 12) under reduced duration, suggesting greater physiological plasticity and adaptability to shortened growing windows. Similar genotype-specific responses to crop duration and environmental stress have been reported in pigeonpea and other legumes (Craufurd *et al.*, 2003; Saxena *et al.*, 2010) [8].

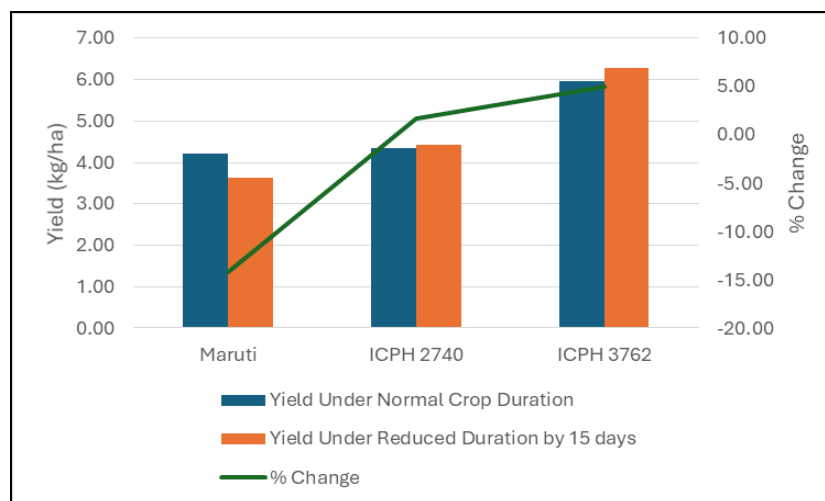


Fig 12: Predicted yield under normal and reduced crop duration

In rainfed systems, where delayed monsoon onset, early withdrawal, and prolonged cloud cover are common, adjusting crop duration becomes critical for minimizing exposure to terminal stresses (Lobell *et al.*, 2011) [25]. One practical approach to achieving this is through transplanted pigeonpea, which enables earlier crop establishment and effectively reduces field duration while maintaining growth advantages. Transplanting helps synchronize crop phenology with favorable weather conditions, particularly avoiding excess rainfall and cloud cover during flowering and pod development stages (Rao *et al.*, 2015) [30].

The integration of ML-based yield prediction further strengthens this approach by enabling accurate estimation of yield outcomes under altered crop durations and management scenarios. By incorporating key variables such as rainfall distribution, cloud cover, and sowing or transplanting time, ML models can simulate and predict genotype performance under shortened duration conditions (Jeong *et al.*, 2016; Kamilaris & Prenafeta-Boldú, 2018) [18, 22].

Together, these findings suggest that combining genotype selection (preference for adaptable hybrids), transplanting techniques, and ML-based predictive tools can serve as an effective strategy for climate risk mitigation. This integrated approach enables optimization of crop duration, reduces exposure to climatic stresses, and improves yield stability under rainfed conditions.

Conclusions

This study pioneers an integrated framework that combines climate diagnostics, farmer perceptions, Failure Mode and Effects Analysis (FMEA), and Machine Learning (ML) to identify risks in rainfed pigeonpea production in Odisha, India. Excessive monsoon rainfall (>200 mm/month) and extended periods of cloud cover (>80% of days) during reproductive stages emerged as key biophysical constraints, supporting farmer-reported yield losses of 10-50%. FMEA identified high-risk failures, such as unfilled pods, pest outbreaks, and moisture deficits, that are strongly linked to climatic variability. Meanwhile, an ML model ($R^2 = 0.982$) delivered accurate, site-specific yield predictions using weather, soil, and farming data.

These findings enable proactive, localized mitigation strategies, from tailored sowing windows to bio-inputs for pest resilience, fostering climate-smart pigeonpea systems. By bridging empirical risk assessment with predictive analytics, this FMEA-ML approach offers a scalable blueprint for safeguarding smallholder

yields amid intensifying climate variability, with transformative potential for regenerative agriculture across South Asia's rainfed domains.

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