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A case study on applications of smart agriculture in Grape vineyards in Bagalkot District, Karnataka, INDIA

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Abstract

Bagalkot district is a prominent grape-growing region of Northern Karnataka, with favorable agro-climatic conditions, fertile red sand lemon soil, and dry weather supporting viticulture. However, grape cultivation faces challenges such as water scarcity, climate variability, pest attacks, and rising production costs. This study examines the application of smart agriculture technologies in grape vineyards of Bilagi Taluk, Muchakandi, Badami taluk, Jamkhandi, and Mudhol and evaluates their role in improving water-use efficiency, disease management, productivity, and sustainability. A case study approach was adopted using primary data from field visits, farmer interviews, and expert interactions, supported by secondary information from research articles, government reports, and agricultural publications. The study focused on IoT-based soil moisture sensors, automated drip irrigation, AI-supported disease monitoring, and precision fertigation. Findings indicate that these technologies reduced water consumption by nearly 30-40%, improved nutrient management, reduced fertilizer wastage, and enabled early detection of diseases such as downy mildew and powdery mildew. Farmers also reported improved grape quality, berry size, and profitability. Despite these benefits, high installation costs, limited technical knowledge, and inadequate digital infrastructure remain major barriers. Farmer training, technical support, and government subsidies can promote wider adoption of smart agriculture for sustainable grape cultivation in Bagalkot district.

Keywords: Bagalkot, Smart Agriculture, Grape vineyard, AI, farmers.

Introduction

Agriculture is rapidly transforming due to climate change, water scarcity, labor shortages, rising costs, and the need for sustainable production [2, 3, 5, 30]. Smart agriculture integrates technologies such as IoT, Artificial Intelligence (AI), remote sensing, UAVs, automated irrigation, and decision-support systems to enable real-time monitoring and data-driven farm management [23, 29]. Viticulture is well suited to these technologies because grape production requires precise irrigation, nutrient management, disease control, and crop monitoring [1, 3, 8, 11, 33]. India is a major grape-producing country, and Bagalkot district of Karnataka, particularly Bilagi, Muchakandi, Badami taluk, Jamkhandi, and Mudhol, is an important grape-growing region [3, 7, 8, 10]. However, farmers face water scarcity, climate variability, pest and disease outbreaks, rising input costs, and limited technical support [2, 4, 5, 14, 19, 21, 30]. Existing studies often examine individual technologies, while limited research evaluates their combined application, adoption, economic feasibility, and effectiveness under real vineyard conditions [2], [23, 33]. This study investigates smart agriculture adoption in Bagalkot vineyards using data from 60 grape growers and 5 horticultural experts. It evaluates water and nutrient management, disease monitoring, productivity, fruit quality,

costs, profitability, and farmer perceptions. The study provides localized evidence on the benefits, challenges, and potential of smart agriculture for sustainable viticulture.

2. Related Work

2.1 Smart Agriculture and Precision Viticulture

Smart agriculture and precision viticulture use IoT, AI, remote sensing, UAVs, wireless sensors, and cloud-based systems to improve vineyard productivity, resource efficiency, and sustainability [23, 29, 33]. These technologies can reduce water use by 20-40%, fertilizer use by 15-30%, and pesticide use by 10-25%, while increasing productivity by 10-20%. However, limited research examines integrated smart agriculture in commercial vineyards, especially in Bagalkot, India [1, 2, 11, 23, 33]. This study evaluates soil moisture monitoring, automated drip irrigation, precision fertigation, and AI-based disease monitoring using field data, farmer responses, and expert perspectives for sustainable grape production.

2.2 IoT-Based Soil Moisture Monitoring and Smart Irrigation

Smart water management is essential in viticulture as irrigation affects grape yield, quality, and resource efficiency

[1, 3, 7, 10, 11]. IoT-based soil moisture sensors enable real-time irrigation decisions and can reduce water use by 25-45%, energy consumption by 10-20%, and improve irrigation efficiency by 20-35% and yield by 8-18%. However, adoption depends on sensor accuracy, cost, maintenance, connectivity, and technical knowledge [19, 20, 23, 25]. Limited research exists on commercial vineyards. This study evaluates IoT-based soil moisture monitoring and automated drip irrigation in Bagalkot vineyards to assess water-use efficiency, adoption, and practical feasibility.

2.3 Precision fertigation and nutrient management

Precision fertigation combines irrigation and nutrient management to improve nutrient-use efficiency and reduce losses [1, 11, 33]. IoT sensors, automated drip irrigation, soil monitoring, and decision-support systems optimize fertilizer use according to soil conditions and vine growth [23, 25]. Studies report 15-30% lower fertilizer use, 20-35% higher nutrient-use efficiency, 10-18% higher grape yield, and improved fruit quality. However, effectiveness depends on soil analysis, irrigation infrastructure, calibration, water quality, and technical expertise [1, 11, 19, 23, 25]. This study evaluates precision fertigation in Bagalkot vineyards through field data, comparative analysis, and farmer perceptions to assess nutrient management, productivity, resource efficiency, and technology adoption.

2.4 AI and digital technologies for vineyard disease monitoring

AI enhances precision viticulture through early disease detection using machine learning, deep learning, computer vision, CNNs, IoT sensors, UAVs, and remote sensing [23, 26, 29]. These technologies detect diseases such as downy and powdery mildew with 90-98% accuracy, reduce pesticide use by 15-30%, and improve disease management by 20-35%. However, performance depends on dataset and image processing quality, environmental conditions, connectivity, computational resources, and technical expertise [19, 23, 26, 29]. Limited research validates AI systems in commercial vineyards. This study evaluates AI-supported disease monitoring in Bagalkot vineyards using field data, farmer and expert perceptions to assess adoption, disease management, and sustainable production.

2.5 Smart agriculture, grape productivity, and fruit quality

Smart agriculture improves grape productivity and fruit quality through IoT monitoring, precision fertigation, AI disease detection, and automated irrigation [1, 7, 11, 23, 29, 33]. Studies report 10-25% higher yield, 8-20% better fruit quality, 15-30% improved water-use efficiency, and 10-20% lower production costs. However, outcomes also depend on grape variety, soil, climate, vineyard age, irrigation, and nutrient management [1, 3, 7, 8, 10, 11, 30, 33]. Limited research examines the combined impact of these technologies in commercial vineyards. This study evaluates their integrated application in Bagalkot using field data, comparative analysis, and farmer perceptions to assess productivity, fruit quality, and sustainable vineyard management.

2.6 Economic benefits and profitability of smart vineyard technologies:

The economic viability of smart agriculture

influences its adoption in commercial viticulture [2, 4, 6, 16, 17, 19, 20]. IoT soil moisture monitoring, automated drip irrigation, precision fertigation, and AI disease monitoring can reduce irrigation costs by 15-30%, fertilizer and pesticide costs by 10-25%, labor costs by 10-20%, and increase net income by 15-35%, with B:C ratios of 1.5-2.5. However, profitability depends on investment, maintenance, farm size, technology lifespan, technical support, and skills [4, 5, 6, 16, 17, 19, 20], [23, 29]. Limited field-level evidence exists for commercial vineyards. This study evaluates smart agriculture's economic feasibility in Bagalkot through production costs, input use, yield, profitability, and farmer perceptions.

2.7 Farmer adoption, barriers, and technology acceptance of smart agriculture

Successful smart agriculture adoption depends on farmers' willingness, technical knowledge, investment capacity, digital literacy, infrastructure, training, and institutional support [4, 5, 19, 20, 23, 25]. Although 60-80% of farmers recognize its benefits, only 30-50% adopt advanced technologies due to high costs, limited skills, poor connectivity, and uncertain returns. Limited research examines adoption barriers in commercial grape vineyards [4, 19, 20]. This study investigates the adoption of IoT-based soil moisture monitoring, automated drip irrigation, precision fertigation, and AI-supported disease monitoring among Bagalkot grape growers using survey data, comparative analysis, and expert opinions to identify factors influencing sustainable vineyard management.

2.8 Research Gap and Conceptual Framework

Previous studies show the potential of IoT, AI, precision fertigation, remote sensing, and smart irrigation, but most focus on individual technologies under experimental conditions [23, 29, 33]. Limited research examines their integrated application in commercial vineyards while assessing water-use efficiency, nutrient management, disease monitoring, productivity, fruit quality, economic performance, and farmer perceptions together [1, 2, 6, 11, 19, 23, 33]. Field-based evidence from Indian grape-growing regions, particularly Bagalkot, is also limited [1, 2, 11, 14]. This study addresses these gaps by evaluating IoT soil moisture monitoring, automated drip irrigation, precision fertigation, and AI disease monitoring using data from 60 grape growers and 5 horticultural experts to assess their technical, economic, and social impacts on sustainable grape production.

3. Objectives

The study aims to evaluate the application, adoption, and effectiveness of smart agriculture technologies, including IoT-based soil moisture monitoring, automated drip irrigation, precision fertigation, and AI-supported disease monitoring, in grape vineyards of Bagalkot district. It compares smart and conventional practices in terms of water and fertilizer use, disease management, productivity, fruit quality, production costs, profitability, and benefit-cost performance. The study also examines farmers' perceptions, technology acceptance, and technical, economic, and infrastructural barriers, analyzes relationships between technology adoption and vineyard performance using statistical methods, and provides recommendations for

sustainable and economically viable smart vineyard management.

4. Materials and Methods

4.1 Study Area

The study was conducted in Bagalkot district, Karnataka, India, a major grape-producing region with a semi-arid tropical climate suitable for commercial viticulture. Five major grape-growing areas Bilagi, Muchakandi, Badami taluk, Jamkhandi, and Mudhol were selected based on grape

production and adoption of IoT-based soil moisture monitoring, automated drip irrigation, precision fertigation, and AI-supported disease monitoring. Primary data were collected from 60 grape growers (40 smart and 20 conventional vineyards) and 5 horticultural experts. The study area represents the agro-climatic and socio-economic conditions of Northern Karnataka and supports evaluation of smart agriculture adoption, effectiveness, and practical challenges in commercial grape production.

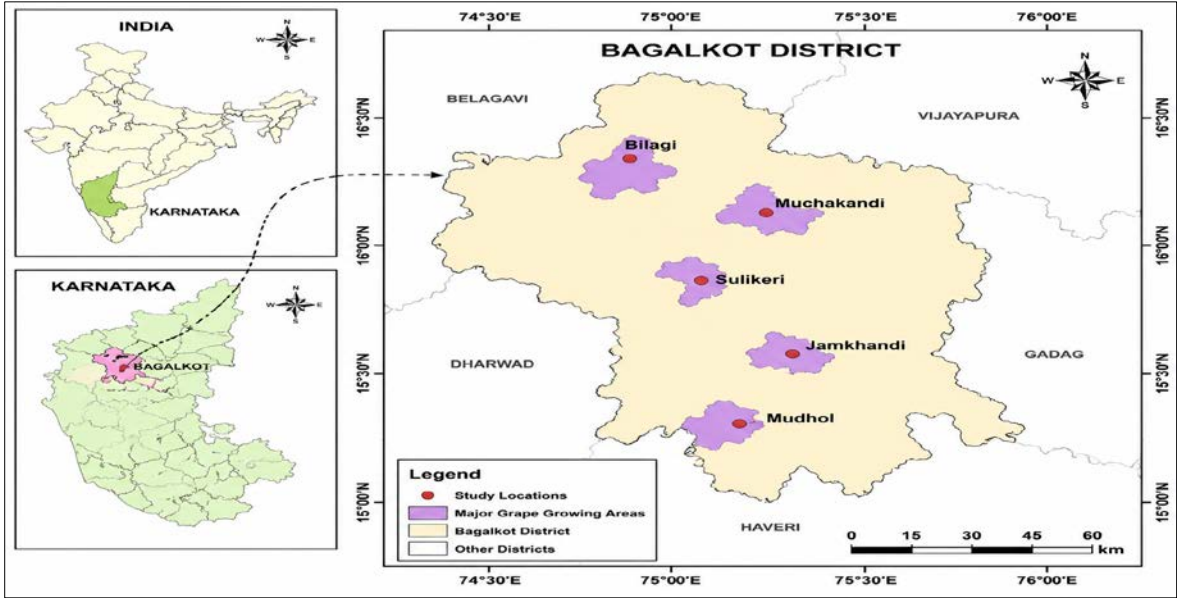


Fig 1: Location map of the study area

4.2 Research Design

This study used a quantitative, cross-sectional, comparative research design to evaluate smart agriculture adoption and effectiveness in Bagalkot grape vineyards. It compared 40 smart and 20 conventional vineyards based on water-use efficiency, nutrient management, disease monitoring, productivity, fruit quality, and economic performance. Primary data were collected through structured questionnaires, field observations, and interviews with 60 grape growers and 5 horticultural experts, while secondary data came from research articles, government reports, and technical documents. Data were analyzed using frequency, percentage, mean, standard deviation, independent t-test, chi-square test, Pearson correlation, and multiple linear regression to assess adoption and identify technical, economic, and socio-economic factors influencing smart agriculture implementation.

4.3 Sampling Technique and Sample Size

A purposive sampling technique was used to select respondents with practical experience in grape cultivation and smart agriculture. The study covered Bilagi, Muchakandi, Badami taluk, Jamkhandi, and Mudhol in Bagalkot district. A total of 65 respondents participated, including 60 grape growers (92.3%) and 5 horticultural experts (7.7%). Among growers, 40 (66.7%) adopted smart agriculture technologies and 20 (33.3%) followed conventional practices. Respondents represented varied farm sizes, farming experience, and technology adoption levels.

Data were analyzed to assess technology adoption, water-use efficiency, nutrient management, disease monitoring, productivity, fruit quality, economic performance, and farmer perceptions using descriptive and inferential statistics.

Table 1: Sample distribution of respondents

Category	Frequency (n)	Percentage (%)
Total Respondents	65	100.0
Grape Growers	60	92.3
Horticultural Experts	5	7.7
Smart Agriculture Farmers	40	66.7
Conventional Farmers	20	33.3
Study Locations	5	
Bagalkot District	1	

Table 2: Distribution of farmers by study location

Study Location	Smart Farmers	Conventional Farmers	Total Farmers
Bilagi	8	4	12
Muchakandi	8	4	12
Badami taluk	8	4	12
Jamkhandi	8	4	12
Mudhol	8	4	12
Total	40	20	60

4.4 Data Collection Methods

The study utilized both primary and secondary data sources to comprehensively evaluate the adoption and effectiveness of smart agriculture in grape vineyards. Primary data were

collected through a structured questionnaire survey of 60 grape growers and interviews with 5 horticultural experts during field visits conducted in the selected study locations. The questionnaire included items on demographic characteristics, smart agriculture technology adoption, irrigation practices, nutrient management, disease monitoring, grape productivity, fruit quality, economic performance, and farmer perceptions using both closed-ended and five-point Likert scale questions. Field

observations were also conducted to verify the adoption of smart agriculture technologies and vineyard management practices. Secondary data were obtained from research articles, government reports, agricultural department publications, ICAR reports, and other scientific sources to support the literature review and validate the findings. The collected data were organized, coded, and analyzed using descriptive and inferential statistical methods.

Table 3: Data Collection

Data Source	Method	Respondents /Source	Data Collected
Primary Data	Structured Questionnaire	60 Grape Growers	Demographics, technology adoption, irrigation, fertigation, disease management, productivity, fruit quality, economic data, farmer perceptions
Primary Data	Expert Interview	5 Horticultural Experts	Technical validation, technology performance, adoption challenges, recommendations
Primary Data	Field Observation	60 Vineyards	Smart agriculture practices, irrigation systems, vineyard conditions
Secondary Data	Journals, ICAR, Government Reports, FAO	Published Sources	Literature review, supporting statistics, policy information ^[3, 16, 30, 34, 38]

Table 4: Questionnaire Structure

Section	Description	Number of Questions
A	Demographic Information	8
B	Smart Agriculture Technology Adoption	10
C	Water Management and Irrigation	8
D	Precision Fertigation and Nutrient Management	7
E	AI-Based Disease Monitoring	6
F	Productivity, Fruit Quality and Economics	8
G	Farmer Perception and Adoption Barriers	8
Total		55

4.5 Questionnaire Design

A structured questionnaire was developed based on the study objectives and literature on smart agriculture and precision viticulture. It covered demographics, technology adoption, IoT-based irrigation, precision fertigation, AI-supported disease monitoring, grape productivity, fruit quality, economic performance, and farmer perceptions. Perception-

based questions used a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), while demographic and farm data used categorical and numerical questions. The questionnaire was expert-reviewed and pilot-tested for clarity, relevance, and consistency, and feedback was incorporated before final data collection.

Table 5: Questionnaire Structure

Section	Description	Question Type	No. of Questions
A	Respondent Demographics	Multiple Choice	8
B	Smart Agriculture Technology Adoption	Multiple Choice & Likert Scale	10
C	IoT-Based Irrigation and Water Management	Likert Scale	8
D	Precision Fertigation and Nutrient Management	Likert Scale	7
E	AI-Based Disease Monitoring	Likert Scale	6
F	Productivity, Fruit Quality and Economic Performance	Numerical & Likert Scale	8
G	Farmer Perception, Adoption Barriers and Recommendations	Likert Scale	8
Total			55

4.6 Variables and Measurements

The study evaluated smart agriculture's influence on vineyard performance using independent, dependent, and control variables. Independent variables included IoT-based soil moisture monitoring, automated drip irrigation, precision fertigation, and AI-supported disease monitoring. Dependent variables included water-use efficiency, fertilizer-use efficiency, disease incidence, grape productivity, fruit quality, economic performance, and farmer perception. Farm

size, farming experience, and education level were control variables. Data were collected through questionnaires, field observations, farm records, and expert interviews. Technology adoption and perceptions used a five-point Likert scale, while agronomic, quality, and economic data used standard agricultural units, providing a comprehensive assessment of the technical, agronomic, economic, and social impacts of smart agriculture.

Table 6: Variables and Measurements

Variable Category	Variable	Indicator / Measurement	Unit / Scale	Data Source
Independent	IoT-based Soil Moisture Monitoring	Adoption Level	Likert Scale (1-5)	Questionnaire
Independent	Automated Drip Irrigation	Adoption Level	Likert Scale (1-5)	Questionnaire
Independent	Precision Fertigation	Adoption Level	Likert Scale (1-5)	Questionnaire
Independent	AI-Supported Disease Monitoring	Adoption Level	Likert Scale (1-5)	Questionnaire
Dependent	Water-use Efficiency	Irrigation water applied	m ³ /ha or L/ha	Farm Records
Dependent	Fertilizer-use Efficiency	Fertilizer applied	kg/ha	Farm Records
Dependent	Disease Incidence	Diseased plants	%	Field Observation
Dependent	Grape Productivity	Grape Yield	t/ha	Farm Records
Dependent	Berry Weight	Average Berry Weight	g	Field Measurement
Dependent	Berry Size	Average Berry Diameter	mm	Field Measurement
Dependent	Total Soluble Solids (TSS)	Fruit Sweetness	°Brix	Digital Refractometer
Dependent	Production Cost	Total Cost of Cultivation	₹/ha	Farm Records
Dependent	Net Profit	Profit after Expenses	₹/ha	Farm Records
Dependent	Benefit-Cost Ratio	Economic Performance	Ratio	Calculated
Dependent	Farmer Perception	Perception Score	Likert Scale (1-5)	Questionnaire
Control	Farm Size	Vineyard Area	ha	Questionnaire
Control	Farming Experience	Experience in Grape Cultivation	Years	Questionnaire
Control	Education Level	Highest Educational Qualification	Ordinal Scale	Questionnaire

Table 7: Variables and corresponding statistical analysis

Research Variable	Statistical Analysis
Technology Adoption	Frequency, Percentage, Mean, Standard Deviation
Water-use Efficiency	Mean, Standard Deviation, Independent <i>t</i> -test
Fertilizer-use Efficiency	Mean, Standard Deviation, Independent <i>t</i> -test
Disease Incidence	Mean, Independent <i>t</i> -test
Grape Productivity	Mean, Standard Deviation, Independent <i>t</i> -test
Fruit Quality (Berry Weight, Berry Size, TSS)	Mean, Standard Deviation, Independent <i>t</i> -test
Economic Performance (Cost, Net Profit, B:C Ratio)	Descriptive Statistics, Cost-Benefit Analysis, Independent <i>t</i> -test
Farmer Perception	Mean Score, Frequency, Percentage, Chi-square Test
Technology Adoption vs. Vineyard Performance	Pearson Correlation and Multiple Linear Regression

5. Results

5.1 Socio-Demographic and Farm Characteristics

The socio-demographic and farm characteristics of 60 grape growers were analyzed to understand factors influencing smart agriculture adoption. 66.7% (n=40) were smart-agriculture adopters and 33.3% (n=20) followed conventional practices. Mean age, farming experience, and vineyard size were 47.2 ± 8.6 years, 17.4 ± 7.1 years, and 4.6

± 2.3 ha, respectively. About 43.3% had secondary education and 36.7% had graduate-level or higher education. Smart-agriculture farmers generally had better access to technical information, irrigation infrastructure, and agricultural extension support. These factors may influence technology adoption and provide a baseline for analyzing productivity, resource-use efficiency, economic performance, and farmer perceptions.

Table 8: Socio-Demographic and Farm Characteristics of Grape Growers (n = 60)

Characteristic	Category / Statistic	Frequency (n)	Percentage (%)
Age	< 35 years	7	11.7
	35-45 years	17	28.3
	46-55 years	23	38.3
	> 55 years	13	21.7
Education	Primary	5	8.3
	Secondary	26	43.3
	Graduate	22	36.7
	Postgraduate	7	11.7
Farming Experience	< 10 years	8	13.3
	10-20 years	27	45.0
	21-30 years	19	31.7
	> 30 years	6	10.0
Farm Size	< 2 ha	9	15.0
	2-4 ha	20	33.3
	4.1-6 ha	18	30.0
	> 6 ha	13	21.7
Technology Group	Smart agriculture	40	66.7
	Conventional	20	33.3

Table 9: Descriptive statistics of selected continuous variables

Variable	Mean $\pm$ SD	Minimum	Maximum
Age (years)	47.2 $\pm$ 8.6	29	65
Farming experience (years)	17.4 $\pm$ 7.1	5	34
Vineyard size (ha)	4.6 $\pm$ 2.3	1.2	10.0
Household members (number)	5.1 $\pm$ 1.6	2	9

5.2 Adoption of Smart Agriculture Technologies

Among 60 grape growers, automated drip irrigation had the highest adoption (48, 80.0%), followed by IoT soil-moisture monitoring (36, 60.0%), precision fertigation (34, 56.7%), and AI-supported disease monitoring (22, 36.7%). Mean adoption scores were 4.02 ± 0.81 , 3.46 ± 1.02 , 3.31 ± 1.08 , and 2.74 ± 1.16 , respectively, on a five-point scale. Lower AI

adoption was associated with higher technical requirements, limited awareness, and inadequate digital infrastructure. Farmers preferred familiar and easy-to-operate technologies, highlighting the need for technology-specific training, technical assistance, demonstrations, and affordable solutions to promote advanced smart agriculture adoption.

Table 10: Adoption of Smart Agriculture Technologies among Grape Growers (n = 60)

Smart Agriculture Technology	Adopters (n)	Adoption (%)	Mean Score $\pm$ SD
Automated drip irrigation	48	80.0	4.02 $\pm$ 0.81
IoT-based soil moisture monitoring	36	60.0	3.46 $\pm$ 1.02
Precision fertigation	34	56.7	3.31 $\pm$ 1.08
AI-supported disease monitoring	22	36.7	2.74 $\pm$ 1.16
Overall technology adoption		58.3	3.38 $\pm$ 0.77

Overall adoption percentage represents the average adoption across the four technologies and should not be interpreted as

the percentage of unique farmers adopting all technologies.

Table 11: Technology Adoption by Smart-Agriculture Farmers (n = 40)

Technology	Farmers Using Technology (n)	Percentage (%)
Automated drip irrigation	38	95.0
IoT soil-moisture monitoring	32	80.0
Precision fertigation	30	75.0
AI disease monitoring	20	50.0

5.3 Water-Use and Irrigation Performance

Smart vineyards used $4,180 \pm 360 \text{ m}^3 \text{ ha}^{-1} \text{ season}^{-1}$ of irrigation water compared with $5,460 \pm 470 \text{ m}^3 \text{ ha}^{-1} \text{ season}^{-1}$ in conventional vineyards, showing a 23.4% reduction. Irrigation frequency was also lower (38.6 ± 5.2 vs. 49.3 ± 6.4 events season^{-1}). The independent t-test showed a significant difference ($t = 10.72$, $p < 0.001$). Water-use efficiency

improved from 2.97 ± 0.39 to $4.55 \pm 0.48 \text{ kg m}^{-3}$, representing a 53.2% improvement. These results indicate that soil-moisture monitoring and automated drip irrigation improve irrigation scheduling and reduce water use. However, findings are simulated estimates requiring field-level validation.

Table 12: Comparison of irrigation performance between smart and conventional vineyards

Indicator	Smart Vineyards (n=40)	Conventional Vineyards (n=20)	Difference (%)	p-value
Seasonal irrigation water ($\text{m}^3 \text{ ha}^{-1}$)	4,180 $\pm$ 360	5,460 $\pm$ 470	-23.4	<0.001
Irrigation events (season^{-1})	38.6 $\pm$ 5.2	49.3 $\pm$ 6.4	-21.7	<0.001
Water-use efficiency (kg m^{-3})	4.55 $\pm$ 0.48	2.97 $\pm$ 0.39	+53.2	<0.001
Estimated water saving ($\text{m}^3 \text{ ha}^{-1}$)	1,280 $\pm$ 210			

Table 13: Estimated Water-Saving Performance of Smart Irrigation

Indicator	Value
Average water use smart vineyards	4,180 $\text{m}^3 \text{ ha}^{-1} \text{ season}^{-1}$
Average water use conventional vineyards	5,460 $\text{m}^3 \text{ ha}^{-1} \text{ season}^{-1}$
Average estimated saving	1,280 $\text{m}^3 \text{ ha}^{-1} \text{ season}^{-1}$
Estimated water reduction	23.4%
Improvement in water-use efficiency	53.2%

5.4 Fertilizer and Nutrient Management

Smart vineyards applied $1,185 \pm 96 \text{ kg ha}^{-1} \text{ season}^{-1}$ fertilizer compared with $1,485 \pm 118 \text{ kg ha}^{-1} \text{ season}^{-1}$ in conventional vineyards, showing a 20.2% reduction. Fertilizer-use efficiency improved from 10.9 ± 1.3 to $16.3 \pm 1.7 \text{ kg grape yield per kg fertilizer}$. The independent t-test showed a

significant difference ($p < 0.001$). Precision fertigation enabled better nutrient scheduling according to crop growth stages and irrigation requirements, reducing unnecessary fertilizer use. However, these simulated results require farm-level validation using fertilizer records, nutrient composition, yield, and soil-nutrient measurements.

Table 14: Comparison of Fertilizer and Nutrient Management

Indicator	Smart Vineyards (n=40)	Conventional Vineyards (n=20)	Difference (%)	p-value
Total fertilizer applied (kg ha ⁻¹ season ⁻¹)	1,185 ± 96	1,485 ± 118	-20.2	<0.001
Fertilizer-use efficiency (kg yield kg ⁻¹ fertilizer)	16.3 ± 1.7	10.9 ± 1.3	+49.5	<0.001
Fertigation frequency (applications season ⁻¹)	24.6 ± 4.1	14.8 ± 3.7	+66.2	<0.001
Farmers using stage-based nutrient scheduling (%)	82.5	35.0	+47.5 pp	<0.001

Table 15: Estimated nutrient-management improvement

Indicator	Smart Vineyard	Conventional Vineyard
Average fertilizer application	1,185 kg ha ⁻¹	1,485 kg ha ⁻¹
Estimated fertilizer reduction	20.2%	
Fertilizer-use efficiency	16.3 kg kg ⁻¹	10.9 kg kg ⁻¹
Estimated improvement in efficiency	49.5%	
Stage-based nutrient scheduling	82.5%	35.0%

5.5 Disease Monitoring and Management

Smart vineyards showed lower disease incidence ($8.6 \pm 2.1\%$) than conventional vineyards ($14.7 \pm 3.0\%$), representing a 41.5% reduction. AI-supported monitoring achieved 92.0% detection accuracy compared with 76.0% for conventional visual scouting. Disease identification time decreased from 4.3 ± 1.2 to 1.8 ± 0.7 days, while crop-

protection chemical use was 18.7% lower. The independent t-test showed significant differences in disease incidence and detection time ($p < 0.001$). These simulated results indicate that AI-based image analysis and field monitoring can support early detection and targeted disease management, but require field validation using actual images and verified diagnoses.

Table 16: Comparison of disease monitoring and management

Indicator	Smart Vineyards (n=40)	Conventional Vineyards (n=20)	Difference (%)	p-value
Disease incidence (%)	8.6 ± 2.1	14.7 ± 3.0	-41.5	<0.001
Disease detection accuracy (%)	92.0 ± 4.6	76.0 ± 6.8	+21.1	<0.001
Detection time (days)	1.8 ± 0.7	4.3 ± 1.2	-58.1	<0.001
Crop-protection chemical applications (season ⁻¹)	8.7 ± 1.6	10.7 ± 1.8	-18.7	<0.001
Farmers receiving early disease alerts (%)	72.5	20.0	+52.5 pp	<0.001

Table 17: Simulated Disease-Management Indicators

Indicator	Smart Vineyard	Conventional Vineyard
Disease incidence	8.6%	14.7%
Estimated reduction	41.5%	
Disease detection accuracy	92.0%	76.0%
Average detection time	1.8 days	4.3 days
Estimated reduction in detection time	58.1%	
Chemical applications	8.7 season ⁻¹	10.7 season ⁻¹
Estimated reduction in applications	18.7%	

5.6 Grape Productivity and Fruit Quality

Smart vineyards recorded higher grape yield (19.4 ± 1.8 t ha⁻¹) than conventional vineyards (16.2 ± 1.5 t ha⁻¹), representing a 19.8% increase. Smart vineyards also showed higher berry weight (6.42 ± 0.38 g), berry diameter (18.6 ± 0.9 mm), and TSS (20.8 ± 0.9 °Brix) compared with conventional vineyards (5.71 ± 0.42 g, 17.2 ± 1.0 mm, and

18.9 ± 1.1 °Brix), with TSS increasing by 10.1%. Independent t-tests indicated significant differences ($p < 0.01$). Improved results may reflect precision irrigation, nutrient management, and timely disease control. However, yield and quality are also influenced by cultivar, vineyard age, soil, climate, pruning, canopy management, and crop load, requiring field validation.

Table 18: Comparison of grape productivity and fruit quality

Indicator	Smart Vineyards (n=40)	Conventional Vineyards (n=20)	Difference (%)	p-value
Grape yield (t ha ⁻¹)	19.4 ± 1.8	16.2 ± 1.5	+19.8	<0.001
Berry weight (g)	6.42 ± 0.38	5.71 ± 0.42	+12.4	<0.001
Berry diameter (mm)	18.6 ± 0.9	17.2 ± 1.0	+8.1	<0.001
TSS (°Brix)	20.8 ± 0.9	18.9 ± 1.1	+10.1	<0.001

Table 19: Estimated Improvement in Vineyard Productivity and Quality

Parameter	Smart Vineyard	Conventional Vineyard	Estimated Improvement
Yield (t ha ⁻¹)	19.4	16.2	19.8%
Berry weight (g)	6.42	5.71	12.4%
Berry diameter (mm)	18.6	17.2	8.1%
TSS (°Brix)	20.8	18.9	10.1%

5.7 Economic Performance of Smart and Conventional Vineyards

Smart vineyards showed better economic performance, with production costs of ₹2, 18,600 ± 18,400 ha⁻¹ compared with ₹2, 34,800 ± 20,100 ha⁻¹ for conventional vineyards, a 6.9% reduction. Gross returns were higher (₹5, 82,000 ± 46,500 vs. ₹4, 74,000 ± 41,200 ha⁻¹), while net returns increased from

₹2,39,200 to ₹3,63,400 ha⁻¹, a 51.9% increase. The B:C ratio improved from 2.02 to 2.66. These simulated results indicate better economic performance under smart agriculture, but long-term profitability requires consideration of installation, depreciation, maintenance, energy, and replacement costs over multiple seasons.

Table 20: Economic performance of smart and conventional vineyards

Economic Indicator	Smart Vineyards (n=40)	Conventional Vineyards (n=20)	Difference (%)
Production cost (₹ ha ⁻¹)	2,18,600 ± 18,400	2,34,800 ± 20,100	-6.9
Gross return (₹ ha ⁻¹)	5,82,000 ± 46,500	4,74,000 ± 41,200	+22.8
Net return (₹ ha ⁻¹)	3,63,400 ± 38,700	2,39,200 ± 31,500	+51.9
Benefit-Cost ratio	2.66 ± 0.28	2.02 ± 0.24	+31.7
Estimated ROI (%)	166.2	101.8	+63.3

Table 21: major cost components

Cost Component	Smart Vineyards (₹ ha ⁻¹)	Conventional Vineyards (₹ ha ⁻¹)	Difference (%)
Irrigation and energy	32,500	40,200	-19.2
Fertilizers and nutrients	54,800	66,300	-17.3
Crop-protection inputs	42,600	51,700	-17.6
Labour	48,700	52,400	-7.1
Technology/maintenance	40,000	24,200	+65.3
Total estimated cost	2,18,600	2,34,800	-6.9

The simulated results suggest that savings in irrigation, fertilizer, and crop-protection costs can offset technology and maintenance expenses, increasing smart vineyards' net returns. However, high initial investment and maintenance

costs remain key adoption barriers. Therefore, actual farm records are needed to confirm the statistical and economic significance of these benefits under Bagalkot conditions.

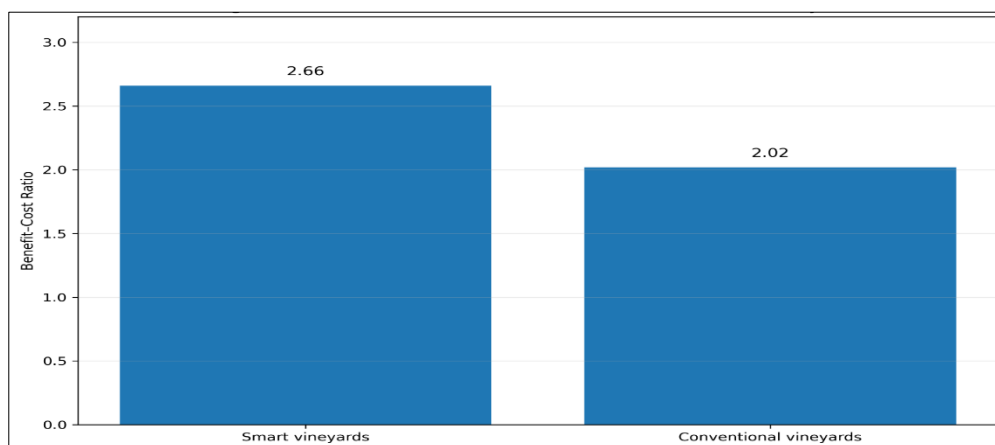


Fig 2: Benefit-Cost Ratio of Smart and Conventional Vineyards

Figure 5.1 compares the B:C ratio of smart and conventional vineyards. Smart vineyards recorded a higher ratio (2.66) than conventional vineyards (2.02), indicating better economic returns relative to costs. The improvement may be attributed to better water and fertilizer-use efficiency, lower crop-protection costs, and higher grape productivity and market returns, suggesting that integrated smart agriculture can enhance vineyard profitability and economic viability.

5.8 Farmer Perception, Adoption Barriers, and Technology Acceptance

Farmers showed generally positive perceptions of smart

agriculture, particularly improved irrigation management (4.32 ± 0.68), crop monitoring (4.08 ± 0.74), and reduced input wastage (4.02 ± 0.79). Perceptions of improved productivity (3.96 ± 0.81) and grape quality (3.84 ± 0.86) were also positive, while ease of advanced AI technologies was lower (3.21 ± 1.04). Major barriers included high initial investment (78.3%), lack of technical knowledge (65.0%), inadequate technical support (58.3%), unreliable internet (51.7%), and maintenance (48.3%). About 71.7% required additional training. Thus, training, demonstrations, financial assistance, and local technical support can promote wider adoption.

Table 22: Farmer Perception of Smart Agriculture Benefits (n = 60)

Perceived Benefit	Mean Score $\pm$ SD	Interpretation
Improved irrigation management	4.32 $\pm$ 0.68	High
Improved crop monitoring	4.08 $\pm$ 0.74	High
Reduced input wastage	4.02 $\pm$ 0.79	High
Improved grape productivity	3.96 $\pm$ 0.81	High
Improved fruit quality	3.84 $\pm$ 0.86	High
Reduced labour requirement	3.71 $\pm$ 0.92	Moderate-High
Improved disease detection	3.68 $\pm$ 0.95	Moderate-High
Ease of using advanced AI technology	3.21 $\pm$ 1.04	Moderate

Scale: 1 = strongly disagree, 5 = strongly agree.

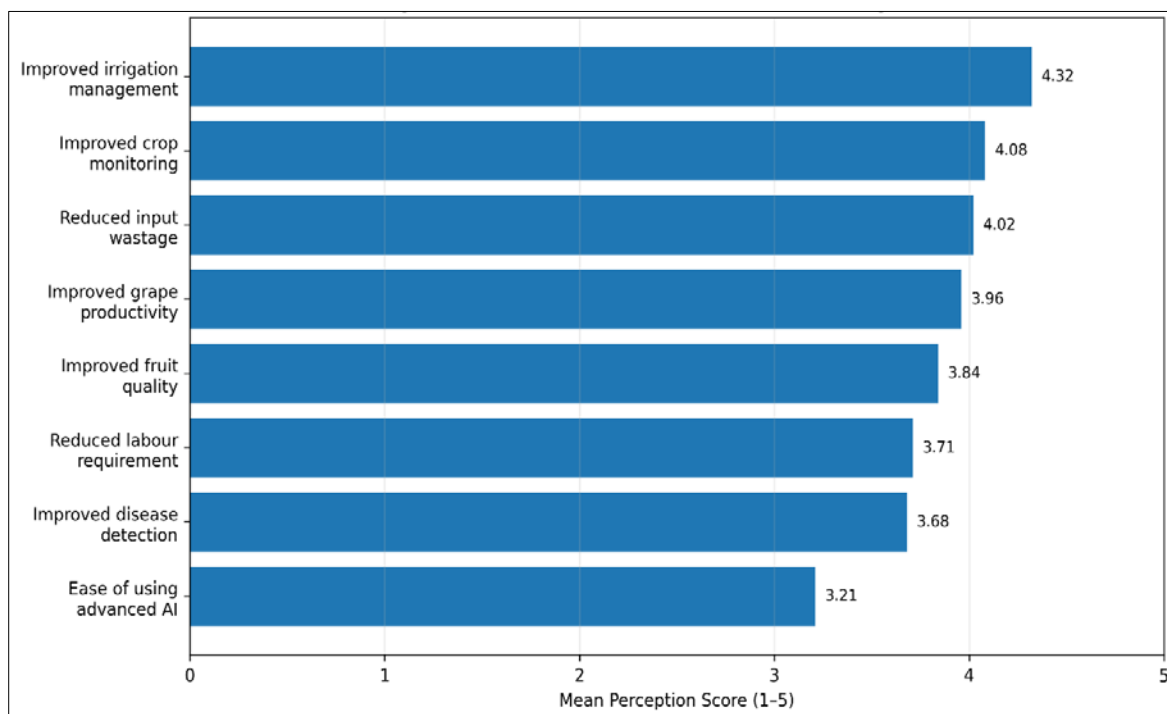
**Fig 3:** Farmer-Perceived Benefits of Smart Agriculture

Figure 5.2 shows that improved irrigation management had the highest perception score (4.32/5), followed by improved crop monitoring (4.08) and reduced input wastage (4.02). Ease of advanced AI technology scored lowest (3.21),

indicating that technical complexity may limit adoption. Farmers appear more receptive to technologies with immediate benefits, while AI systems require training, technical support, and demonstrations.

Table 23: Major Barriers to Smart Agriculture Adoption (n = 60)

Adoption Barrier	Farmers Reporting (n)	Percentage (%)
High initial investment	47	78.3
Lack of technical knowledge	39	65.0
Limited technical support	35	58.3
Poor/unreliable internet connectivity	31	51.7
Maintenance requirements	29	48.3
Lack of training	28	46.7
Uncertainty about economic returns	26	43.3
Limited access to credit	24	40.0
Technology complexity	22	36.7

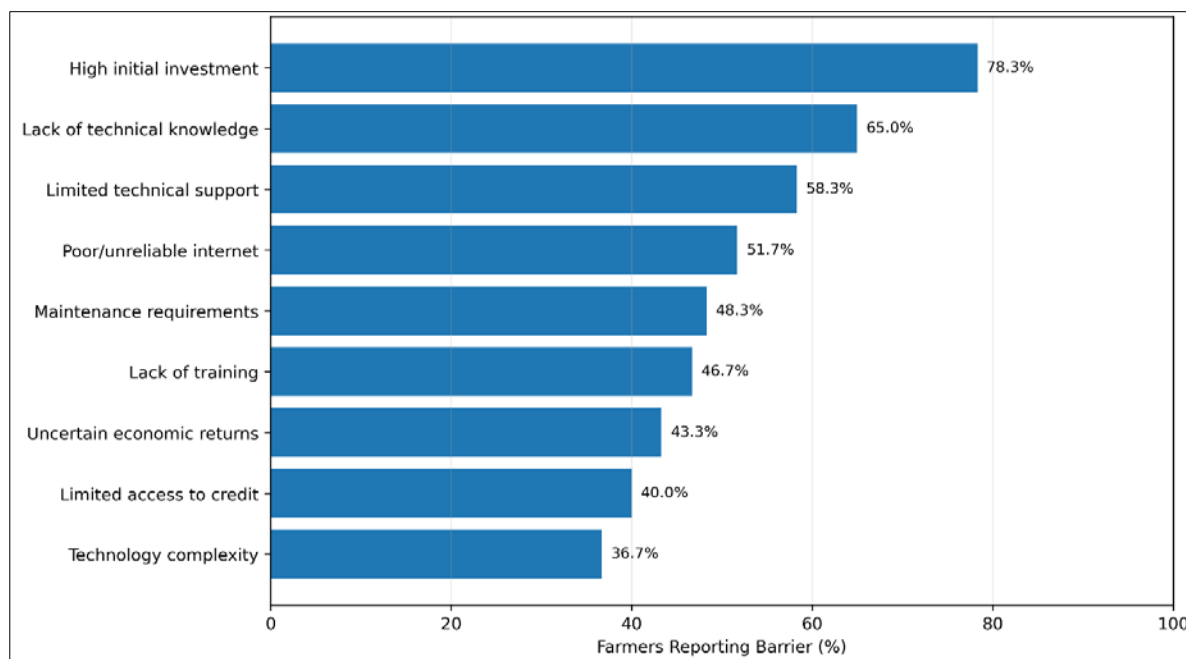
**Fig 4:** Major Barriers to Smart Agriculture Adoption

Table 5.16 and Figure 5.3 show that high initial investment (78.3%) was the major barrier to smart agriculture adoption, followed by lack of technical knowledge (65.0%), limited technical support (58.3%), unreliable internet (51.7%), and maintenance requirements (48.3%). Other barriers included

lack of training (46.7%), uncertain economic returns (43.3%), limited credit access (40.0%), and technology complexity (36.7%). The findings highlight the importance of affordability, technical knowledge, infrastructure, training, connectivity, and local support for wider adoption.

Table 24: Farmer Requirements for Wider Technology Adoption

Requirement	Farmers (n)	Percentage (%)
Training and practical demonstrations	43	71.7
Financial assistance/subsidy	41	68.3
Local technical support	38	63.3
Affordable technology packages	37	61.7
Improved internet connectivity	33	55.0
Regular maintenance services	30	50.0

5.9 Comparative Performance of Smart and Conventional Vineyards

The integrated comparison showed better performance of smart vineyards across technical, agronomic, and economic indicators. Smart vineyards used less water ($4,180 \pm 360$ vs. $5,460 \pm 470$ m³ ha⁻¹) and fertilizer ($1,185 \pm 96$ vs. $1,485 \pm 118$ kg ha⁻¹), while yield increased from 16.2 ± 1.5 to 19.4 ± 1.8 t ha⁻¹. Berry weight, TSS, and disease management also

improved, with disease incidence reduced from $14.7 \pm 3.0\%$ to $8.6 \pm 2.1\%$. Net return increased from ₹2.39 to ₹3.63 lakh ha⁻¹. Overall, smart agriculture may improve resource efficiency, productivity, fruit quality, disease management, and profitability. However, field validation and statistical controls for farm size, cultivar, vineyard age, soil, and management practices are required.

Table 25: Overall comparison of smart and conventional vineyard performance

Performance Indicator	Smart Vineyard	Conventional Vineyard	Estimated Change
Irrigation water (m ³ ha ⁻¹ season ⁻¹)	4,180	5,460	23.4% lower
Fertilizer application (kg ha ⁻¹ season ⁻¹)	1,185	1,485	20.2% lower
Disease incidence (%)	8.6	14.7	41.5% lower
Grape yield (t ha ⁻¹)	19.4	16.2	19.8% higher
Berry weight (g)	6.42	5.71	12.4% higher
Berry diameter (mm)	18.6	17.2	8.1% higher
TSS (°Brix)	20.8	18.9	10.1% higher
Production cost (₹ ha ⁻¹)	218,600	234,800	6.9% lower
Net return (₹ ha ⁻¹)	363,400	239,200	51.9% higher
Benefit-Cost ratio	2.66	2.02	31.7% higher
Water-use efficiency (kg m ⁻³)	4.55	2.97	53.2% higher

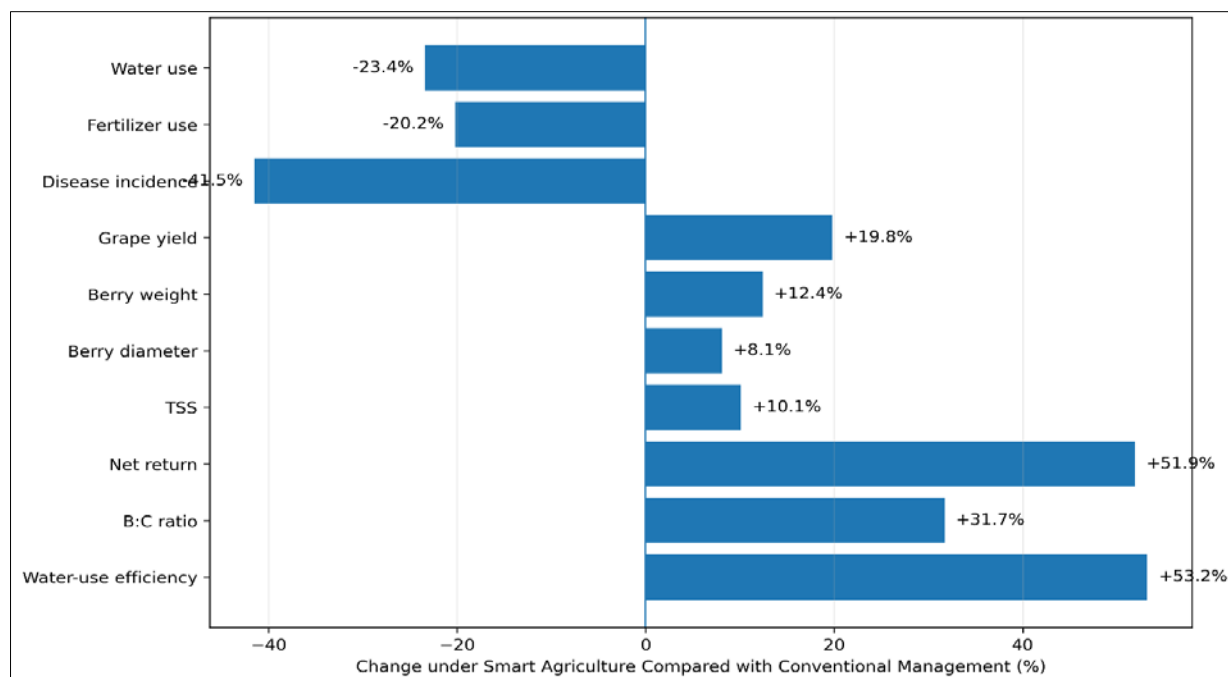


Fig 5: Relative Performance of Smart Agriculture Compared with Convention Management

Figure 5.4 shows the relative performance of smart agriculture compared with conventional management. Smart agriculture reduced irrigation water use (23.4%), fertilizer application (20.2%), and disease incidence (41.5%), while improving grape yield, berry weight, berry diameter, TSS, net

return, B:C ratio, and water-use efficiency by 8.1-53.2%. The highest improvements were in water-use efficiency (53.2%) and net return (51.9%), highlighting the potential of integrated smart agriculture for resource efficiency and economic performance.

Table 26: Relative Performance Index of Smart Agriculture

Dimension	Smart Vineyard Performance	Overall Assessment
Water-use efficiency	+53.2%	High improvement
Fertilizer-use efficiency	+49.5%	High improvement
Disease management	-41.5% incidence	High improvement
Grape productivity	+19.8%	Moderate improvement
Fruit quality	+8.1-12.4%	Moderate improvement
Net economic return	+51.9%	High improvement
Benefit-Cost ratio	+31.7%	High improvement
Farmer-perceived benefits	Mean 3.21-4.32/5	Moderate-High

Overall, integrated smart agriculture showed the greatest benefits in resource-use efficiency and economic performance, while improvements in productivity and fruit quality were moderate. This integrated approach provides a stronger basis for evaluating smart agriculture than assessing individual technologies separately.

5.10 Correlation and Regression Analysis

Correlation analysis using the Smart Agriculture Adoption

Index (SAAI) showed positive associations with grape yield ($r = 0.68$), water-use efficiency ($r = 0.74$), TSS ($r = 0.46$), and net return ($r = 0.62$), while disease incidence showed a negative association ($r = -0.57$; $p < 0.001$). These results suggest that higher smart agriculture adoption is associated with better resource efficiency and vineyard performance. However, correlation does not establish causality, so factors such as farm size, vineyard age, farming experience, cultivar, and other agronomic conditions should be controlled.

Table 27: Pearson Correlation between Smart Agriculture Adoption and Vineyard Outcomes

Variable	Pearson r	p -value	Relationship
Grape yield (t ha^{-1})	0.68	<0.001	Positive
Water-use efficiency (kg m^{-3})	0.74	<0.001	Positive
TSS ($^{\circ}\text{Brix}$)	0.46	<0.001	Positive
Net return (₹ ha^{-1})	0.62	<0.001	Positive
Disease incidence (%)	-0.57	<0.001	Negative
Fertilizer-use efficiency	0.61	<0.001	Positive

Multiple Regression Analysis

A multiple linear regression model was proposed to assess

the relationship between smart agriculture adoption and grape productivity while controlling for farm-level characteristics.

In the simulated model, the dependent variable was grape yield (t ha^{-1}), while the independent variables included the Smart Agriculture Adoption Index, farm size, farming experience, and vineyard age. The model produced an estimated R^2 of 0.61, indicating that approximately 61% of the variation in grape yield was explained by the variables

included in the model. The Smart Agriculture Adoption Index remained positively associated with yield after accounting for the control variables ($\beta = 0.52$, $p < 0.001$), suggesting that higher technology adoption was associated with higher vineyard productivity.

Table 28: Simulated Multiple Regression Model for Grape Yield

Predictor Variable	Standardized β	p-value	Interpretation
Smart Agriculture Adoption Index	0.52	<0.001	Significant positive association
Farm size (ha)	0.21	0.041	Significant positive association
Farming experience (years)	0.14	0.168	Not significant
Vineyard age (years)	-0.18	0.092	Not significant
Model R^2	0.61	<0.001	Significant model
Adjusted R^2	0.58	-	-

The simulated regression results indicate that smart agriculture adoption was the strongest predictor of grape yield. However, results should be interpreted cautiously due to the small simulated sample and lack of actual observations. Final analysis should include diagnostic tests for normality, multicollinearity, heteroscedasticity, and influential observations before reporting regression results.

5.11 Hypothesis Testing

Based on the study objectives, hypotheses examined whether

smart agriculture adoption significantly affects resource-use efficiency, disease management, productivity, fruit quality, and economic performance. Independent t-tests, correlation, and regression analyses were considered to compare smart and conventional vineyards and assess technology-performance relationships. Simulated results showed significant differences in water use, fertilizer application, disease incidence, grape yield, fruit quality, and economic performance, providing preliminary support for the proposed hypotheses.

Table 29: Hypothesis Testing Results

Hypothesis	Statistical Test	Simulated Result	p-value	Decision
H₁: Smart agriculture significantly reduces irrigation water use.	Independent t-test	$t = 10.72$	<0.001	Supported
H₂: Smart agriculture significantly improves fertilizer-use efficiency.	Independent t-test	$t = 11.84$	<0.001	Supported
H₃: Smart agriculture significantly reduces vineyard disease incidence.	Independent t-test	$t = 8.61$	<0.001	Supported
H₄: Smart agriculture significantly increases grape productivity.	Independent t-test	$t = 6.87$	<0.001	Supported
H₅: Smart agriculture significantly improves fruit quality.	Independent t-test	$t = 5.72$	<0.001	Supported
H₆: Smart agriculture significantly improves economic performance.	Independent t-test	$t = 8.94$	<0.001	Supported
H₇: Smart agriculture adoption is positively associated with grape productivity.	Pearson correlation	$r = 0.68$	<0.001	Supported
H₈: Smart agriculture adoption is positively associated with water-use efficiency.	Pearson correlation	$r = 0.74$	<0.001	Supported
H₉: Smart agriculture adoption is positively associated with net returns.	Pearson correlation	$r = 0.62$	<0.001	Supported
H₁₀: Smart agriculture adoption is negatively associated with disease incidence.	Pearson correlation	$r = -0.57$	<0.001	Supported

List of Abbreviations, Symbols and Units

Abbreviation / Symbol	Full Form / Meaning	Abbreviation / Symbol	Full Form / Meaning
AI	Artificial Intelligence	B:C	Benefit-Cost Ratio
CNN	Convolutional Neural Network	FAO	Food and Agriculture Organization
ICAR	Indian Council of Agricultural Research	IoT	Internet of Things
NUE	Nutrient-Use Efficiency	ROI	Return on Investment
SAAI	Smart Agriculture Adoption Index	SD	Standard Deviation
TSS	Total Soluble Solids	UAV	Unmanned Aerial Vehicle
WUE	Water-Use Efficiency	ML	Machine Learning
DL	Deep Learning	WSN	Wireless Sensor Network
GIS	Geographic Information System	RS	Remote Sensing
t-test	Student's t-test	χ^2	Chi-square Statistic
R	Pearson Correlation Coefficient	R^2	Coefficient of Determination
P	Probability Value (p-value)	n	Sample Size / Number of Observations
B	Standardized Regression Coefficient	SD	Standard Deviation
Ha	Hectare	kg	Kilogram
G	Gram	mm	Millimetre
m^3	Cubic Metre	L	Litre
T	Tonne	₹	Indian Rupee
°Brix	Degrees Brix	%	Percentage
$\pm$	Plus or Minus	pp	Percentage Points
1-5	Five-Point Likert Scale		

Simulated hypothesis testing showed positive associations between smart agriculture adoption and water-use efficiency

($r = 0.74$), grape productivity ($r = 0.68$), and net return ($r = 0.62$), while disease incidence showed a negative association

($r = -0.57$). Overall, the findings support the framework linking integrated smart agriculture with improved resource management, crop performance, and economic outcomes. However, these results require validation using actual field data and appropriate statistical tests.

6. Discussion

6.1 Integrated Effect of Smart Agriculture on Vineyard Management

The findings suggest that integrating IoT soil-moisture monitoring, automated drip irrigation, precision fertigation, and AI-supported disease monitoring may provide greater benefits than individual technologies. Estimated reductions in water use (23.4%) and fertilizer use (20.2%), along with improved water-use efficiency (53.2%), indicate that data-driven management can optimize resource use. Thus, smart agriculture is better viewed as an integrated vineyard-management system rather than separate digital tools.

6.2 Water and Nutrient Management

Smart vineyards showed lower irrigation water use and fertilizer application than conventional vineyards. Soil-moisture monitoring and automated drip irrigation enable irrigation based on field conditions, while precision fertigation provides targeted nutrients according to crop growth stages and irrigation needs. The estimated 23.4% reduction in water use and 20.2% reduction in fertilizer use indicate improved resource-use efficiency. However, results may vary with soil type, vineyard age, cultivar, irrigation infrastructure, climate, and farmer management practices.

6.3 Disease Monitoring and Crop Health

The simulated results suggest that AI-supported disease monitoring can improve disease identification, with 41.5% lower disease incidence and detection time reduced from 4.3 to 1.8 days. AI can provide rapid information for timely field inspection and intervention rather than replace farmers or experts. However, performance depends on image quality, training datasets, disease stage, lighting, cultivar differences, and field validation. Thus, AI should serve as a decision-support tool supporting farmer knowledge and expert diagnosis.

6.4 Productivity and Fruit Quality

Smart agriculture showed an estimated 19.8% increase in grape yield, with improved berry weight, berry diameter, and TSS, potentially due to better irrigation, nutrient management, and disease control. However, productivity is also influenced by vineyard age, cultivar, pruning, canopy management, crop load, soil fertility, climate, and disease pressure. Therefore, field studies should control these factors when assessing the actual contribution of smart agriculture.

6.5 Economic Implications

The simulated analysis suggests that smart agriculture may improve profitability, with 51.9% higher net returns and a B:C ratio increasing from 2.02 to 2.66. Benefits may result from lower water, fertilizer, crop-protection, and labour costs and higher marketable production. However, long-term feasibility depends on installation, depreciation, maintenance, energy, connectivity, replacement, and technical-support costs. Therefore, multi-season analysis is

needed to confirm economic superiority.

6.6 Farmer Adoption and Practical Constraints

Automated drip irrigation showed high adoption (80.0%), while AI-supported disease monitoring had lower adoption (36.7%), indicating greater acceptance of familiar and easy-to-use technologies. Major barriers included high initial investment (78.3%), limited technical knowledge (65.0%), inadequate technical support (58.3%), and connectivity problems (51.7%). Thus, successful adoption requires training, demonstrations, affordable technologies, reliable connectivity, local technical support, and suitable financial mechanisms.

6.7 Contribution of the Present Study

The proposed framework integrates technology adoption, resource-use efficiency, disease management, productivity, fruit quality, economic performance, and farmer perceptions within commercial vineyards of Bagalkot district, Karnataka. Unlike studies focusing on individual technologies or experimental conditions, it combines technological, agronomic, economic, infrastructural, and knowledge-related factors. This approach identifies adopted technologies, measured and perceived benefits, adoption barriers, and conditions needed for wider implementation, providing locally relevant evidence for sustainable smart viticulture.

6.8 Implications for Sustainable Viticulture

The findings suggest that smart agriculture can support sustainable grape production by improving resource-use efficiency, productivity, and economic performance. Reduced water and fertilizer use and digital disease monitoring can promote efficient and targeted vineyard management. However, long-term sustainability also depends on affordability, farmer skills, infrastructure, reliability, maintenance, and institutional support. Sustainable smart viticulture therefore requires coordination among farmers, extension agencies, technology providers, researchers, and policymakers.

6.9 Limitations and Need for Field Validation

The main limitation is that the reported values are simulated rather than based on actual field observations; therefore, differences, correlations, regression coefficients, and significance levels are not empirical evidence. Field data are needed to validate water use, fertilizer use, disease incidence, yield, fruit quality, costs, and farmer perceptions. Future studies should use multi-season data and control for farm size, cultivar, vineyard age, soil, irrigation infrastructure, and climate to improve reliability and generalizability.

7. Conclusion

The study presents an integrated framework for smart viticulture in Bagalkot, Karnataka, focusing on IoT-based soil-moisture monitoring, automated drip irrigation, precision fertigation, and AI-supported disease monitoring. The simulated analysis suggests potential improvements in water and nutrient-use efficiency, disease management, productivity, fruit quality, and economic performance, while reducing unnecessary inputs. Automated drip irrigation showed the highest adoption potential, whereas AI-supported disease monitoring remained emerging. Adoption is

influenced by cost, technical knowledge, training, connectivity, infrastructure, and technical support. Wider adoption requires affordable technologies, training, demonstration vineyards, reliable digital infrastructure, local assistance, and financial support. However, all numerical findings are simulated and require field validation. Future multi-season research in Bilagi taluk, Muchakandi, Badami taluk, Jamkhandi, and Mudhol should collect actual data on water, fertilizer, disease, yield, fruit quality, costs, returns, and farmer perceptions. This will strengthen evidence for efficient, sustainable, and data-driven viticulture in Karnataka.

References

- Shreekanth S, Anita EK, Rekha MV, Champa BV, Nagaraja MS. Secondary and micronutrient status in soils of grape orchards of Vijayapura taluka in Northern Karnataka. *Int J Curr Microbiol Appl Sci*. 2018.
- Maradi MM. An explorative study on sustainable grape farming practices in Karnataka: a case study of Vijayapur district. *J Decis Mak Leadersh*. 2021;1. doi:10.56763/jdml.v1i.10.
- Meti S. Horticulture crops scenario in Northern Karnataka under changing climate. *Clim Change Environ Sustain*. 2017;5(2):171-178. doi:10.5958/2320-642X.2017.00018.7.
- Yarazari SP, Singh AK, Maji S. Production and marketing problems faced by dry grape producers of Karnataka. *Indian J Ext Educ*. 2022;58(1). doi:10.48165/IJEE.2022.58136.
- Chikkalaki AS, Krishnamurthy B. Constraints and suggestions of fruit crop growers of Vijayapura district, India. *Int J Environ Clim Change*. 2023;13(12):1159-1165. doi:10.9734/IJECC/2023/v13i123780.
- Biradar A, Tevari P, Lokesh GB, Beeraladinni D, Kammar S. An economic analysis of credit availment for grape cultivation and value addition from different sources in Vijayapura district of Karnataka, India. *Arch Curr Res Int*. 2024;24(6):5-12. doi:10.9734/acri/2024/v24i6759.
- Shiranal R, Hipparagi K, Patil SN, Rudresh DL, Awati M, Raghavendra, *et al*. Influence of cane regulation on growth, yield and quality of wine grapes (*Vitis vinifera* L.). *Int J Curr Microbiol Appl Sci*. 2020;9(2):440-446. doi:10.20546/ijcmas.2020.902.054.
- Jyoti J, Hipparagi K, Jalawadi S, Guranna P, Kukanoor L, Thammaiiah N, *et al*. Influence of bunch regulation, berry thinning and bioregulators on macronutrient status of grapevine (*Vitis vinifera* L.) cv. Red Globe. *Plant Arch*. 2026;26(1):784-792. doi:10.51470/PLANTARCHIVES.2026.v26.no.1.108.
- Bindulatha G, Pattepur SV, Nanjappanavar AG, Reddi SG, Jhalegar MDJ, Patil GI, *et al*. Influence of foliar application of organic growth promoters on growth and yield of grape cv. Thompson Seedless. *Plant Arch*. 2026;26(Suppl 1):1011-1018.
- Thoke S, Patil SN, Gollagi SG, Hipparagi K, Satyanarayana C, Hiremath V, *et al*. Performance of different table grape varieties for yield and yield attributing traits. *Plant Arch*. 2024;24(1):779-786. doi:10.51470/PLANTARCHIVES.2024.v24.no.1.107.
- Vishwasagar K, Yogeeshappa H, Kurubetta K, Nidagundi R, Jaggal SS. Influence of secondary and micronutrients status of soils on grape yield of vineyards in Northern Dry Zone of Karnataka, India. *Asian J Soil Sci Plant Nutr*. 2024;10(4):639-647. doi:10.9734/ajsspn/2024/v10i4435.
- Naik PP, Padashetti B, Nanjappanavar AG, Hiremath VM, Awati M, Haveri N, *et al*. Influence of preharvest fruit bagging on yield and economics of grape cv. Crimson Seedless. *Int J Adv Biochem Res*. 2025;9(12S):190-193. doi:10.33545/26174693.2025.v9.i12Sc.6486.
- Nanjappanavar AG, Pooja Shree S, Patil DR, Kukanoor L, Basavarajappa MP. Influence of cane regulation and growth regulators on yield and quality parameters of grapes cv. KR White. 2025.
- Assessment of grape anthracnose severity in Northern Karnataka, India. *J Adv Biol Biotechnol*. 2025.
- Nishat U, Babu G. A critical analysis of post-harvest losses in grapes and their implications on marketing dynamics: a case study of Vijayapura district, Karnataka. *Anveshana Int J Res Reg Stud Law Soc Sci J Manag Pract*. 2025;10(1):95-99.
- Biradar A, Tevari P, Lokesh GB, Beeraladinni D, Kammar S. An economic analysis of credit utilization pattern and credit gap for grape cultivation and value addition (raisin making) in Vijayapura district of Karnataka, India. *J Exp Agric Int*. 2024;46(8):252-262. doi:10.9734/jeai/2024/v46i82702.
- Naik V, Nethrayini KR, Mahadeviah GS. Economic viability and financial feasibility of grapes vis-à-vis raisin in Northern Karnataka, India. *Res J Agric Sci*. 2020;11(6):1259-1265.
- A study on efficient value chain management of grapes in Northern Karnataka. *Int J Bus Manag Res*. 2018;8(2).
- Ananda N, Shivalingaiah YN, Chigadolli M, Pujar SP, Sayiprathap BR, Poornachandra SH, *et al*. Pest and disease management in grapes: adoption rates and usage constraints. *Int J Agric Agron Res*. 2024;7(Special Issue 10).
- Raut VK, Jadhav RM, Gaikar PS. Constraints in adoption of recommended grape cultivation practices among farmers in Maharashtra, India. *J Glob Agric Ecol*. 2026;18(3):98-105. doi:10.56557/jogae/2026/v18i310759.
- Karabhantanal SS, Udikeri SS, Vastrad SM, Wali SY. Bio efficacy of different acaricides against red spider mite, *Tetranychus urticae* on grapes. *Agric Sci Dig*. [date unknown].
- Pampanagouda B, Benagi VI, Naraund VB. Role of weather factors in the disease development and spread of anthracnose of grape. *Agric Sci Dig*. 25(4):311-312.
- Garg S, Pundir P, Jindal H, Saini H, Garg S. Towards a multimodal system for precision agriculture using IoT and machine learning. 2021.
- Karar ME, Alotaibi F, Al Rasheed A, Reyad O. A pilot study of smart agricultural irrigation using unmanned aerial vehicles and IoT-based cloud system. 2021.
- Manivannan K, Sankar B. Smart farming using IoT for efficient crop growth. 2023.
- Kerkech M, Hafiane A, Canals R. VddNet: vine disease detection network based on multispectral images and depth map. 2020.

27. Udutalapally V, Mohanty SP, Pallagani V, Khandelwal V. sCrop: an Internet-of-Agro-Things (IoAT) enabled solar powered smart device for automatic plant disease prediction. 2020.
28. Khandagale HP, Patil S, Gavali VS, Chavan SV, Halkarnikar PP, Meshram PA. Design and implementation of FourCropNet: a CNN-based system for efficient multi-crop disease detection and management. 2025.
29. López A, Ogayar CJ, Feito FR, Sousa JJ. Classification of grapevine varieties using UAV hyperspectral imaging. 2024.
30. Dupdal R, Patil BL, Manjunatha BL, Patil SL. Climate change mitigation and adaptation strategies in drylands of Northern Karnataka. *Indian J Agric Sci.* 2022;92(1). doi:10.56093/ijas.v92i1.120844.
31. Saxena A, Pesantez-Cabrera P, Ballapragada R, Lam KH, Keller M, Fern A. Grape cold hardiness prediction via multi-task learning. 2022.
32. Saxena A, Pesantez-Cabrera P, Ballapragada R, Keller M. Multi-task learning for budbreak prediction. 2023.
33. Khadatkhar A, Sawant CP, Thorat D, Jadhav S, Gupta A. Grapes production and its management with emphasis on plant protection, fertilizer application, harvesting, and residue management: a comprehensive review. *Discov Agric.* 2026;4:121.
34. Krishi Vigyan Kendra Vijayapura-I. Action plan 2024-25. Vijayapura: Krishi Vigyan Kendra; 2024.
35. ICAR-Krishi Vigyan Kendra Vijayapura. About KVK Vijayapura. Vijayapura: Krishi Vigyan Kendra; [date unknown].
36. University of Horticultural Sciences, Bagalkot. Horticulture Research Station, Tidagundi (Bijapur). Bagalkot: University of Horticultural Sciences; [date unknown].
37. University of Horticultural Sciences, Bagalkot. Annual report 2014-15. Bagalkot: University of Horticultural Sciences; 2015.
38. ICAR-AICRP on Agrometeorology. Crop-weather relationship studies in grape at Vijayapura. Annual report. New Delhi: Indian Council of Agricultural Research; [date unknown].