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Implications of appropriate technology and farm inputs in the agricultural sector of Gujarat: empirical analysis based on primary data

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Abstract This study examines the usages, benefits, and obstacles in the applications of various technologies, and the impact of appropriate technologies, on agricultural productivity in Gujarat, India. Most farmers are aware of the economic, social, and environmental viability of appropriate technologies and they use these for a variety of purposes. The results imply that agricultural productivity is influenced by many factors, including technology cost, technological development, total arable land, cropping intensity, irrigated area, use of fertilizer and agricultural labour, annual income of farmers, practice of appropriate technologies in cultivation, financial support from government, agricultural co-operative societies, and agricultural extension offices.

JEL codes C21, C31, O14, Q10, Q12, Q16, Q18

Keywords Agricultural productivity, appropriate technology, farm management practices, technological development, sustainable agricultural development

In the 1970s Schumacher introduced the concept of "appropriate technology" (Zhou, Jiao, and Li 2017; Lee et al. 2018; Patnaik and Bhowmick 2018), defined as technology that meets the ecological, cultural, and economic requirements of society (Musunuri 2014). Appropriate technologies are new, small-scale technologies, or ideas or knowledge or knowledge-know-how, that are useful in reducing the negative impact of production activities on economic, social, and environmental sustainability (Moon and Hwang 2018) and that are discovered or invented to meet the basic requirements of a community (Patnaik and Bhowmick 2018).

Being labour-intensive technologies that are useful in creating jobs and improving livelihood security (Lissenden, Maley, and Mehta 2015), appropriate technologies provide for the use of alternative, renewable resources in production activities (Beder 2000) and assist in improving the efficiency of socio-economic and human activities, and energy and material resources, at the micro level (Garniati et al. 2014). Appropriate technologies have brought several benefits to food production, energy, health, sanitation, water, education, service, agriculture, and industry (Dunn 1978; Rohatgi and Rohatgi 1979; Shanthy 2011); for instance, digital technologies and digitalization may be used as an appropriate technology in farming (Mondejar et al. 2021). Appropriate technologies would help in improving the productivity and efficiency of inputs (labour, water, land, human, energy, and finance) without degrading the quality of ecosystem services (Costanza et al. 2012; Garniati et al. 2014; Singh, Narayanan, and Sharma 2019).

High population growth worldwide is increasing the pressure on ecosystem services and the agriculture sector to meet the growing food demand (Singh and Issac 2018; Calicioglu et al. 2019). The world population, now 7.3 billion, would be around 10 billion by 2050 (Talaviya et al. 2020), and providing them all food security will be difficult (Kumar, Ahmad, and Sharma 2017). Developing economies will face several obstacles in creating jobs and in providing food security, social security, and health security; sustaining the environment; and in reducing poverty and income inequality (Kumar 2015; Calicioglu et al. 2019). And these obstacles can be surmounted only with the applications of technological development, such as digital, and appropriate technologies in cultivation, to achieve sustainable agricultural development (Pasa 2017; Talaviya et al. 2020; Mondejar et al. 2021; Ashraf and Singh 2021).

Appropriate technologies would be effective in improving land and cropping patterns; farm management practices and techniques; seed quality, germination, and marketing; and soil quality and fertility (Abdullahi, Mahieddine, and Sheriff 2015; Talaviya et al. 2020). The use of appropriate technologies would help to increase the production of food grains and cash crops, create employment (Talaviya et al. 2020), and contribute to increasing the production of animals, meat, and milk. The application of appropriate technologies will create development opportunities for agriculture, industry, and the livestock rearing, and dairy, services, and energy sectors in countries (Mondejar et al. 2021) and contribute to improving the well-being and livelihood security of farmers and citizens worldwide.

Appropriate technologies have multidimensional aspects, including technology and knowledge transfer, technology mechanisms, and capacity-building across sectors (Lee et al. 2018). Subsequently, technology transfers create entrepreneurship ecosystems, improve access to markets, and commercialize existing technologies (Pearce 2019). Appropriate technologies are a crucial determinant of innovation and technological development (Singh and Bhowmick 2015; Singh et al. 2022). Also, the usage of appropriate technologies in agriculture will create jobs and improve crop productivity and the sustainability of ecosystem services.

The practices of appropriate technologies have brought several alternatives to improving food production and the economic condition of farmers (Dunn 1978; Dhehibi et al. 2020). Appropriate technologies help to improve agricultural productivity, efficiency, and profitability. Using appropriate technologies helps to maintain crop quality and durability and reduce bacteria in agricultural products. In India, for instance, using biotechnology in cultivating cotton increased farmers' profit and reduced the application of chemical fertilizer (Kapur 2018). In largely agrarian economies, technological development may help to improve production, yield, cropped area, and farmers' income (Ashraf and Singh 2021; Kapur 2018).

Science and technology, and technological development, have had a positive impact on the agricultural sector in India (Rohatgi and Rohatgi 1979; Parayil 1992; Desai 1994; Gandhi 1997; Parthasarathy 2002; Larson et al. 2004; Birthal and Kumar 2004; Shanthy 2011; Joshi 2012; Yadav and Goyal 2015; Swain 2016; Shabbir and Yaqoob 2019; Ashraf and Singh 2021).

Applying green revolution technologies, technological development, biotechnologies, irrigation technologies, and farm management practices would help India to improve the production and productivity of food grains and cash crops (Birthal and Kumar 2004; Ashraf and Singh 2021). India needs to use appropriate technologies to improve crop productivity and sustainability in ecosystem services and, therefore, sustainable agricultural development, which will bring about food security and maintain food quality, increase the yield of food grains and cash crops, create jobs, increase profits of farmers, and reduce poverty and income inequality (Saiz-Rubio and Rovira-Mαs 2020; Singh et al. 2022) so that it can feed its population in the near future (Singh, Kumar, and Jyoti 2022).

Several studies conceptually identify the importance of appropriate technologies and technological development in agricultural production activities (Dunn 1978; Birthal and Kumar 2004; Shanthy 2011; Calicioglu et al. 2019; Dhehibi et al. 2020), but no empirical model has been developed to assess the impact of appropriate technologies and other inputs on agricultural productivity in India. This study aims to identify the usages, benefits, and obstacles in the applications of technologies in the agricultural sector; observe farmers' perceptions of appropriate technologies and their components; and examine the impact of appropriate technologies, technological development, agricultural development institutions, and other inputs on agricultural productivity by addressing four research questions.

1. What are the usages, benefits, and obstacles of technological development in the agricultural sector?
2. Do farmers understand the appropriate technologies and their applications?
3. How do appropriate technologies and technological development have a positive impact on agricultural productivity?
4. How can local stakeholders, financial institutions, and agricultural cooperative societies, extension offices, universities, and industries help improve farmers' awareness of appropriate technologies and their practices?

This study uses actual information on the applications of technologies in the agricultural sector to assess the role of appropriate technologies, technological development, and other inputs in the agricultural sector of Gujarat, and it is thus a significant contribution to the existing literature.

The study has several limitations, however: it could not evaluate the role of industry in improving the uptake of appropriate technologies in agriculture, or suggest appropriate ways to apply these, or consider factors such as climatic conditions, geographical location, soil and seed quality, sowing time of seed, irrigation methods, farmer's experience, appropriate marketing, appropriate price of production, government policies and agricultural research and development (R&D)—all of which have a significant impact on agricultural productivity.

Materials and methods

Study area

Gujarat is a highly industrialized state, and it has the lion's share of India's industrial growth. Despite that, around 49% of its workforce is engaged in the agricultural sector (Gulati, Roy, and Hussain 2021). Also, most farming households earn their livelihood from the agricultural and allied sector.

Agricultural growth was high from 2001–02 to 2014–15 (Gulati, Roy, and Hussain 2021). The state has a dominant position in food grains (wheat, maize, bajra, rice, sorghum) and cash crops (sugarcane, groundnut, castor, cotton, rapeseed, mustard, soyabean). The growth of cropped area, production. and yield of food grain and cash crops were observed to be positive due to technological development (Ashraf and Singh 2021). It is expected that the growth of Gujarat's agricultural sector will be positive in future due to the applications of various technologies in farming.

For this study, we selected eight districts—Anand, Banas Kantha, Bharuch, Bhavnagar, Junagadh, Kheda, Surat, and Vadodara—because these contribute around 46% of the agricultural labour, 36% of the agricultural district domestic product, 36.6% of the gross cropped area, 31% of the net area sown, and 44% of the gross irrigated area. These eight districts occupy a significant share of the cropped area of food grains and cash crops and contribute significantly to production: around 35% of wheat, 40% of rice, 41% of jowar, 39% of maize, 65% of bajra, 30% of moong, 58% of arhar, 57% of rapeseed and mustard, 39% of groundnut, 70% of sugarcane, and 63% of potato.

Data collection technique

Two blocks from each district were selected randomly. Thereafter, one village from each block was chosen purposively. Accordingly, 16 villages were identified, and 15 farmers from each village considered for personal face-to-face interviews; therefore, a total of 240 farmers were chosen to collect the desired information.

We conducted the interviews in 2019 from 1 October to 31 December using a well-structured questionnaire. The questionnaire included questions on socio-economic structure, educational profile, physical assets, schooling, physical resources, income-generating occupations, use of technologies in farming, barriers in the applications of appropriate technologies, and the involvement of agricultural development and financial institutions in the agricultural sector.

Dependent and independent variables

Agricultural productivity (ap)

We used farm harvest prices to estimate the economic value of each crop and, accordingly, agricultural productivity, and we used agricultural productivity as the dependent variable in the regression analysis (Kumar, Sharma, and Joshi 2016; Ashraf and Singh 2021).

Age of respondent (ar) and family size of respondent (fs)

Farm management practices, which have a positive impact on agricultural production, improve as the age of a farmer increases (Jamal et al. 2021). Family members also have a positive impact on farming activities.

Education level of respondents (el)

Literate farmers understand appropriate technologies and practices and other agricultural inputs (Kumar, Sharma, and Joshi 2016; Jamal et al. 2021).

Gender of respondents (gr)

Male farmers can be associated with various stakeholders and be members of agricultural development institutions. Thus, the gender of respondents has a crucial contribution in the agricultural sector (Singh and Singh 2019).

Annual income of respondent (ai)

Agricultural production is expected to increase as farmer income increases. High-income farming households can use inputs and technologies to improve returns (Jamal et al. 2021). Hence, annual income has a positive impact on agricultural production.

Total agricultural land (tal)

Agricultural production is not possible without arable land. Hence, total agricultural land was used as an independent variable (Chandio et al. 2021).

Irrigated area (ia) and non-irrigated area (nia)

Irrigated land has a higher yielding capacity than non irrigated land (Kumar, Sharma, and Joshi 2016; Msomba, Ndaki, and Nassary 2021).

Use of agricultural labour (ual)

Human resources are crucial in the agricultural sector, and labour force and agricultural labour have been used to capture its impact (Kumar, Sharma, and Joshi 2016; Chandio et al. 2021).

Use of fertilizer (ugf)

Fertilizers help to maintain soil fertility and quality (Msomba, Ndaki, and Nassary 2021); as the use of fertilizer increases, crop productivity increases.

Number of crops cultivated (cropping intensity) (ci)

Cropping intensity is the ratio of gross cropped area to net sown area, or the efficiency of a specific arable area, or its ability to cultivate several crops in a year; for instance, maize, sorghum, and rice grow in the kharif season and wheat, mustard, and gram grow in the rabi season on the same land. We used the number of crops cultivated during the survey year as an independent variable to capture the impact of cropping intensity on agricultural productivity.

Technological cost (ttc)

We used the cost of technology per hectare as an independent variable to capture the impact of technological development on agricultural productivity (Singh et al. 2022).

Economic viability of technology (evt), social viability of technology (svt), environmental viability of technology (envt), and appropriateness of technology (at)

Appropriate technologies have three aspects: economic, social, and environmental (Musunuri 2014; Lee et al. 2018; Moon and Hwang 2018; Siddick 2019; Bhattacharjya, Kakoty, and Singha 2019; Maynard et al. 2020; Singh et al. 2022). Economic viability can be measured by net present value. A technology has social viability when it does not pose users any risk. Technologies are environmentally viable if they can improve the quality of soil, water, and air, soil fertility, water conservation, energy saving and energy use efficiency, natural biological processes, and biodiversity (Kriesemer, Vichow, and Weinberger 2016). Technical, economic, environmental, and sociopolitical sustainability are also components of appropriate technologies (Kriesemer, Vichow, and Weinberger 2016). We can use the components' indicators to check the viability of appropriate technologies. It is difficult to examine the impact of appropriate technologies (Singh et al. 2022), and so we considered farmers' views on the social, economic, and environmental viability of appropriate technologies to capture their influence on agricultural productivity.

Financial problem (fp) and financial support for government (fsg)

Poor and small farmers cannot afford the high cost of agricultural inputs and technologies. Therefore, small landholders cannot improve productivity. Financial support from the government and credit facilities from the banking sector would help them buy seeds, fertilizers, pesticides, technologies, and other inputs (Msomba, Ndaki, and Nassary 2021) and improve productivity.

Farmers' collaboration with different stakeholders (fas)

Agricultural entrepreneurs, universities, extension offices, cooperative societies, and industry provide farmers skilled and technical support (Jamal et al. 2021). Hence, agricultural developmental institutions are crucial in making agricultural development sustainable (Syan et al. 2019).

Skills and technical support from technology developers or sellers (stsf)

Technology developers also train farmers to operate new technologies in the agricultural sector (Singh et al. 2022). Thus, their involvement would help improve productivity.

Empirical analysis

The primary aim of this study is to estimate the impact of appropriate technologies on agricultural productivity in Gujarat. Thus, the study estimates the economic value of all crops at farm harvest prices cultivated by farmers in a survey year; divides the aggregate economic value of all crops by the gross cropped area to measure agricultural productivity; and uses agricultural productivity as the dependent variable in the regression model.

Earlier studies used different factors to estimate the impact of technological development and change on agricultural production (Hayami and Ruttan 1970; Deb, Mandal, and Dey 1991; Ziberman, Khanna, and Lipper 1997; Grabowski and Self 2006; Kumar, Sharma, and Ambrammal 2015; Gebeyehu 2016; Ali et al. 2017; Singh, Narayanan, and Sharma 2017; Siddick 2019; Jyoti and Singh 2020; Ashraf and Singh 2021).

Agricultural productivity is impacted by respondent gender and age; family size; farmers' annual income and education level; gross cropped area; irrigated and non-irrigated area; agricultural labour; fertilizer and cropping intensity (Deb, Mandal, and Dey 1991; Kumar 2015; Swain 2016; Lee et al. 2018; Siddick 2019; Dhehibi et al. 2020); and financial support from government and agricultural developmental institutions. The empirical investigation considers these factors as explanatory variables.

This study uses the cost of technologies to cultivate all crops as an independent variable, and farmers' opinions on appropriate technologies and their components in binary forms, to examine the impact of each on agricultural productivity. We employed the linear, nonlinear, and log linear regression models to assess the effect of appropriate technologies and other inputs on agricultural productivity. Similar empirical models have been used to examine the impact of climatic factors and agricultural inputs on agricultural productivity in India (Kumar, Ahmad, and Sharma 2017; Jyoti and Singh 2020; Ashraf and Singh 2021; Singh et al. 2022). Our study assumes that agricultural productivity is a function of the cost of technology, appropriate technologies, and other inputs.

$$(ap) = f(ttc, tal, ci, ia, nia, ugf, ual, el, ai, fs, ar, evt, svt, envt, at, fp, fsg, fas, stsf, gr) \quad \ldots(1)$$

where,

ap is agricultural productivity;

ttc is cost of technology,

tal is agricultural land,

ci is cropping intensity,

ia is irrigated area,

nia is non-irrigated area,

ugf is use of fertilizer,

ual is use of agricultural labour,

el is educational level,

ai is annual income,

fs is family size,

ar is age of farmers,

evt is economic viability of technology,

svt is social viability of technology,

envt is environmental viability of technology,

at is appropriateness of technology,

fp is financial problem,

fsg is financial support from government,

fas is farmer's collaboration with various stakeholders,

stsf is skilled and technical support from technology developers, and

gr is gender of farmers in Equation 1 (Table 1).

Table 1 Dependent and independent variables

Variables	Symbol	Units
Agricultural productivity	*ap*	Rs.
Technological cost to cultivate all crops	*ttc*	Number
Total agricultural land	*tal*	Ha.
Number of crops cultivated (cropping intensity)	*ci*	Number
Irrigated area	*ia*	Ha.
Non-irrigated area	*nia*	Ha.
Use of fertilizer	*ugf*	Kg.
Use of agricultural labour	*ual*	Number
Educational level of respondent	*el*	Years
Annual income of respondent	*ai*	Rs.
Family size of respondent	*fs*	Number
Age of respondent	*ar*	Years
Economic viability of technology (1 = Yes and 0 = No)	*evt*	Number
Social viability of technology (1 = Yes and 0 = No)	*svt*	Number
Environmental viability of technology (1 = Yes and 0 = No)	*envt*	Number
Appropriateness of technology (1 = Yes and 0 = No)	*at*	Number
Financial problem (1 = Yes and 0 = No)	*fp*	Number
Financial support from government (1 = Yes and 0 = No)	*fsg*	Number
Farmer's collaboration with different stakeholders (Agri-entrepreneurs, agricultural universities, agricultural extension offices or Krishi Vigyan Kendras (KVKs), co-operative societies, ago-industries) (1 = Yes and 0 = No)	*fas*	Number
Skills & technical support from technology developers or sellers (1 = Yes and 0 = No)	*stsf*	Number
Gender of respondents (1 = Male and 0 = Female)	*gr*	Number

The linear regression model is

$$(ap)_i = \alpha_0 + \alpha_1 (ttc)_i + \alpha_2 (tal)_i + \alpha_3 (ci)_i + \alpha_4 (ia)_i + \alpha_5 (nia)_i + \alpha_6 (ugf)_i + \alpha_7 (ual)_i + \alpha_8 (el)_i + \alpha_9 (ai)_i + \alpha_{10} (fs)_i + \alpha_{11} (ar)_i + \alpha_{12} (evt)_i + \alpha_{13} (svt)_i + \alpha_{14} (envt)_i + \alpha_{15} (at)_i + \alpha_{16} (fp)_i + \alpha_{17} (fsg)_i + \alpha_{18} (fas)_i + \alpha_{19} (stsf)_i + \alpha_{20} (gr)_i + u_i \quad \ldots(2)$$

where,

α_0 is the constant coefficient,

$\alpha_1, \alpha_2, \ldots, \alpha_{20}$ are the regression coefficients of independent variables, and

u_i is the error term in Equation 2.

The log linear regression model is

$$\ln (ap)_i = \beta_0 + \beta_1 \ln (ttc)_\mathrm{i} + \beta_2 \ln (tal)_i + \beta_3 \ln (ci)_i + \beta_4 \ln (ia)_i + \beta_5 \ln (nia)_i + \beta_6 \ln (ugf)_i + \beta_7 \ln (ual)_i + \beta_8 \ln (el)_i + \beta_9 \ln (ai)_i + \beta_{10} \ln (fs)_i + \beta_{11} \ln (ar)_i + \beta_{12} (evt)_i + \beta_{13} (svt)_i + \beta_{14} (envt)_i + \beta_{15} (at)_i + \beta_{16} (fp)_i + \beta_{17} (fsg)_i + \beta_{18} (fas)_i + \beta_{19} (stsf)_i + \beta_{20} (gr)_i + v_i \quad \ldots(3)$$

where,

ln is the natural logarithm of respective variables (except binary variables),

β_0 is constant coefficient;

$\beta_1, \beta_1, \ldots, \beta_{21}$ are the regression coefficient of associated variables; and

v_i is the error term in Equation 3.

The nonlinear regression model is

$$(ap)_i = \gamma_0 + \gamma_1 (ttc)_i + \gamma_2 (Sq\ ttc)_i + \gamma_3 (tal)_i + \gamma_4 (Sq\ tal)_i + \gamma_5 (ci)_i + \gamma_6 (Sq\ ci)_i + \gamma_7 (ia)_i + \gamma_8 (Sq\ ia)_i + \gamma_9 (nia)_i + \gamma_{10} (Sq\ nia)_i + \gamma_{11} (ugf)_i + \gamma_{12} (Sq\ ugf)_i + \gamma_{13} (ual)_i + \gamma_{14} (Sq\ ual)_i + \gamma_{15} (el)_i + \gamma_{16} (Sq\ el)_i + \gamma_{17} (ai)_i + \gamma_{18} (Sq\ ai)_i + \gamma_{19} (fs)_i + \gamma_{20} (Sq\ fs)_i + \gamma_{21} (ar)_i + \gamma_{22} (Sq\ ar)_i + \gamma_{23} (evt)_i + \gamma_{24} (svt)_i + \gamma_{25} (envt)_i + \gamma_{26} (at)_i + \gamma_{27} (fp)_i + \gamma_{28} (fsg)_i + \gamma_{29} (fas)_i + \gamma_{30} (stsf)_i + \gamma_{31} (gr)_i + \bullet_i \quad \ldots(4)$$

Here, *Sq* is the square term of corresponding variables (except binary data); γ_0 is the constant coefficient; γ_1,

$\gamma_2, \ldots, \gamma_{31}$ are the regression coefficients of associated explanatory variables; and $\bullet_i$ is the error term in equation (4).

Selecting the appropriate model

We used the Cronbach α statistical test to check the validity of the collected variables (Syan et al. 2019). Moreover, if a variable has a high variation, it may not be in a normal form (Singh et al. 2022); if the values of skewness and kurtosis for a variable lie between “1 and 1, the variable may be considered to be in a normal form.

As we used the linear, nonlinear, and log linear regression models to assess the impact of appropriate technologies and other inputs on agricultural productivity, we used the Ramsay RESET test to check the appropriate functional form of the proposed models (Singh et al. 2022). We estimated the values of the Akaike Information Criterion (AIC) and Bayesian information criterion (BIC) to check the consistency of the regression coefficients (Singh et al. 2022).

Multi-correlation measures the existence of a linear and exact relationship among the explanatory variables (Singh et al. 2022), so we estimated the value of the variance inflation factor (VIF) to assess the presence of multi-correlation between the explanatory variables in the proposed models (Jyoti and Singh 2020). A specific group of variables that have a mean value of VIF less than 10 were considered in the empirical investigation.

Heteroscedasticity measures the non-constant variance that may be caused to increase non-normality in one or more variables in the model. We applied the Cameron and Trivedi decomposition of the IM test and the Breusch-Pagan/Cook-Weisberg test to recognize the incidence of heteroskedasticity (Jyoti and Singh 2020). SPSS and STATA statistical software were used for the regression analysis.

Discussion

Socio-economic background of farmers

Table 2 provides the socio-economic background (age, family size, educational level, and gender) of the respondents and shows the diversity of the social-economic structure of the respondents in the sample.

Practices of various technologies in the agricultural sector

Farmers were using 63 separate technologies to cultivate food grains and commercial crops (Figure 1). The women friendly fertilizer broadcaster technology has applications in the cultivation of 20 crops.

Several technologies have various usages in the cultivation of 19 crops. Some of these technologies are animal-drawn three-row seed-cum-fertilizer drill; tractor-drawn cultivator tines; zero-till seed-cum-fertilizer drill, and tractor-drawn hydraulic platform for harvesting, pruning, and spraying.

Some of the technologies deemed suitable for the cultivation of 18 crops are animal-drawn bhoram deo seed drill, animal-drawn improved blade harrow, and tractor-operated six-row pneumatic planter and rotary weeder.

Some of the technologies used to grow 14 crops are the animal-drawn IGKV biasi plough, seed-cum-ferti-drill, and three-row inclined plate planter and the motor operated rotary dibber and vacuum seeder.

Table 2 Socio-economic background of respondents

Age (in years)		Family size		Education level		Gender	
Group	Number	Group	Number	Group	Number	Sex	Number
20–29	44	0–3	18	8^{th} Passed	43	Male	234
30–39	82	4– 5	124	10^{th} Passed	41	Female	6
40–49	65	6–8	79	12^{th} Passed	46	-	-
50–59	35	9–10	12	Graduate	71	-	-
60 and above	14	11 and above	7	Postgraduate	39	-	-
Total	240		240		240		240

Source Based on field survey

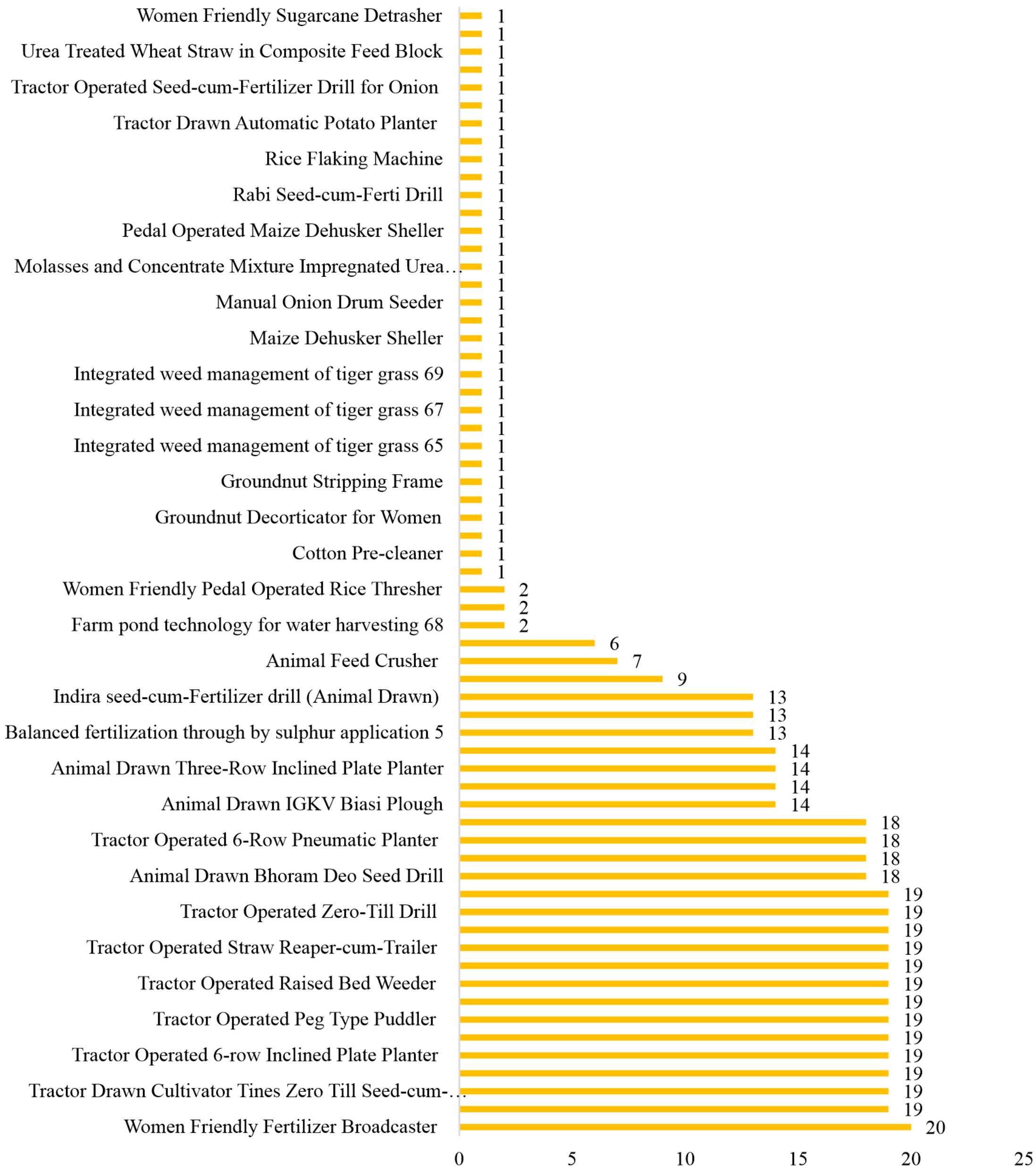

Figure 1 Applications of a specific technology in cultivation of crops (number)
Source Based on field survey

Some of the technologies deemed suitable for the cultivation of 13 crops are balanced fertilization through the application of sulphur and the use of high-capacity multi-crop thresher and Indira seed-cum-fertilizer drill.

Some technologies were applicable for a particular crop only; for instance, gender-friendly rice weeder technology for rice, woman-friendly decorticator for groundnut, dehusker sheller for maize, multi-row manual seed drill for jute, manual drum seeder for onion, comb cutter for banana, pre-cleaner for cotton, and tractor-drawn automatic planter for potato.

Some technologies can be used to cultivate several crops (Figure 2): for instance, 30 technologies can be used for rice; 28 technologies for bajra, cotton, maize, and wheat; 26 for gram, castor seed, groundnut, and moong; 24 for arhar, jowar, math, rapeseed, mustard, and sesamum; 23 for onion; 22 for guar seed, potato,

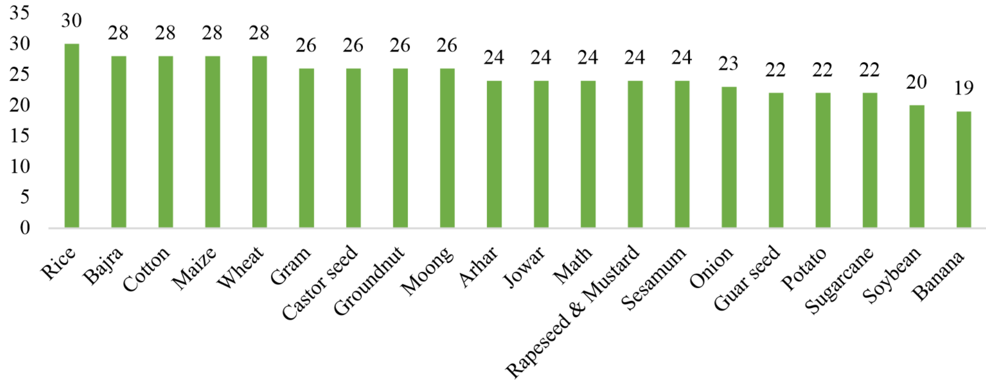

Figure 2 Number of technologies for a particular crop
Source Based on field survey

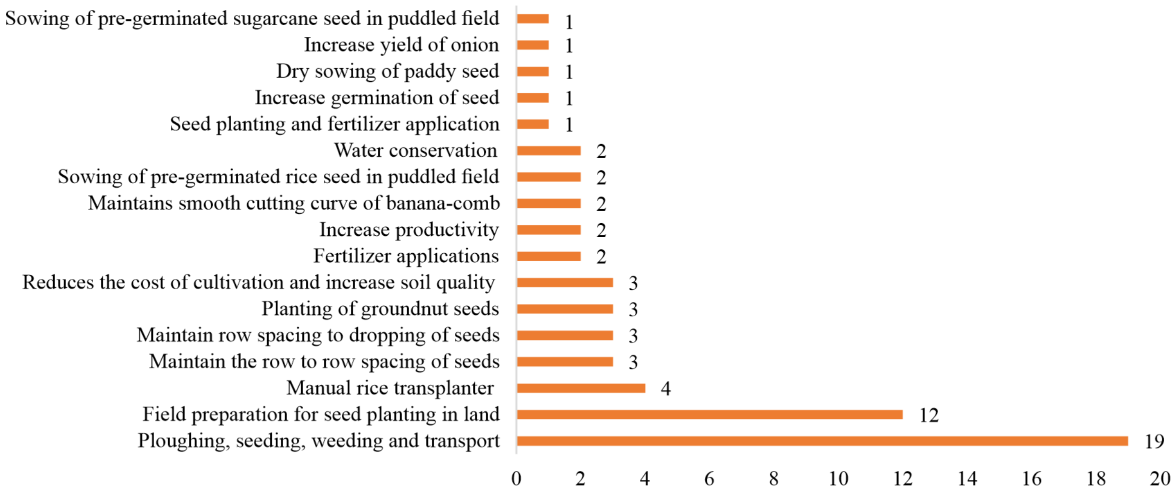

Figure 3 Various usage of technologies in cultivation
Source Based on field survey

and sugarcane; 20 for soyabean; and 19 for banana. These 63 technologies have 494 separate applications in farming food grains and cash crops.

These technologies were grouped into 18 by usage in cultivation (Figure 3): 19 technologies were related to ploughing, seeding, weeding, and transport; 12 to field preparation for seed planning; and 4 technologies to rice cultivation. These technologies were used also for other purposes: manual rice transplanter; maintain the row to row spacing of seeds; maintain row spacing to dropping of seeds; planting of groundnut seeds; and reduce cost of cultivation and increase soil quality.

Benefits of technologies in the agricultural sector

Around 18.33% of the farmers claimed that applying appropriate technologies helped to save water and human effort; 10.83% accepted that technological applications were conducive to preparing the land for seed planting; and 8.3% were unable to provide any answer on the benefits of technologies in cultivation (Figure 4).

Agricultural technologies are understood to have 22 benefits, including a reduction in cultivation cost, water and fertilizer use, labour, and waste material; an improvement in seed germination, yield, marketing, and easy transportation; and the maintenance of farm operations, soil quality and fertility, and soil conservation.

Farmers' problems in applying cultivation technologies

Farmers face several problems in using cultivation technologies (Figure 5).

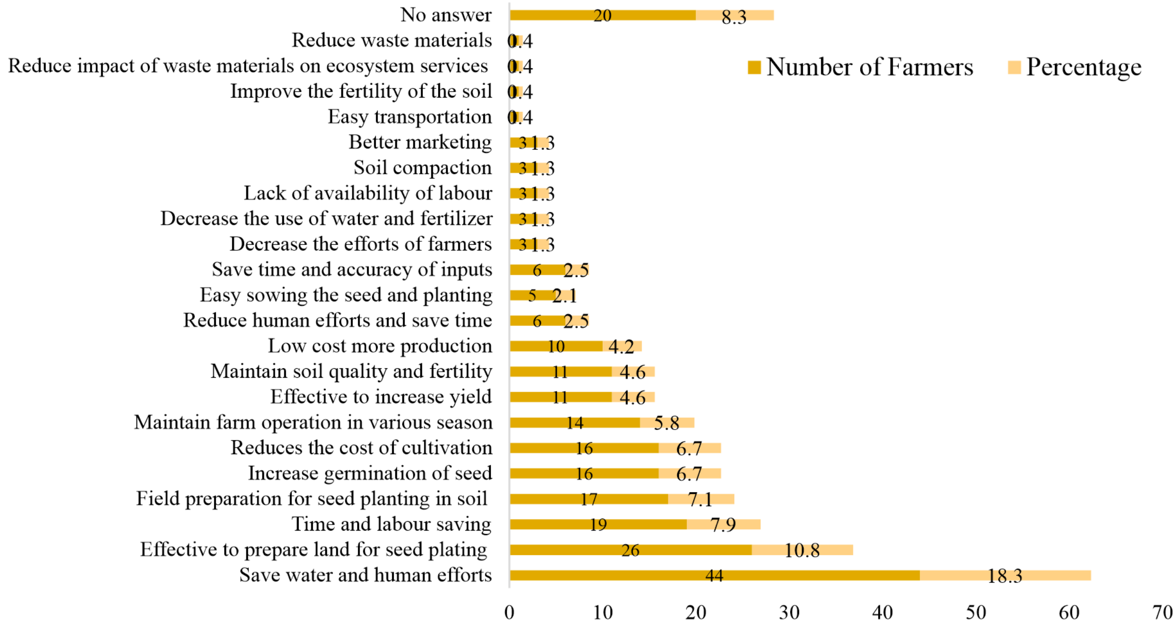

Figure 4 Various advantage of application of technologies in cultivation

Source Based on field survey

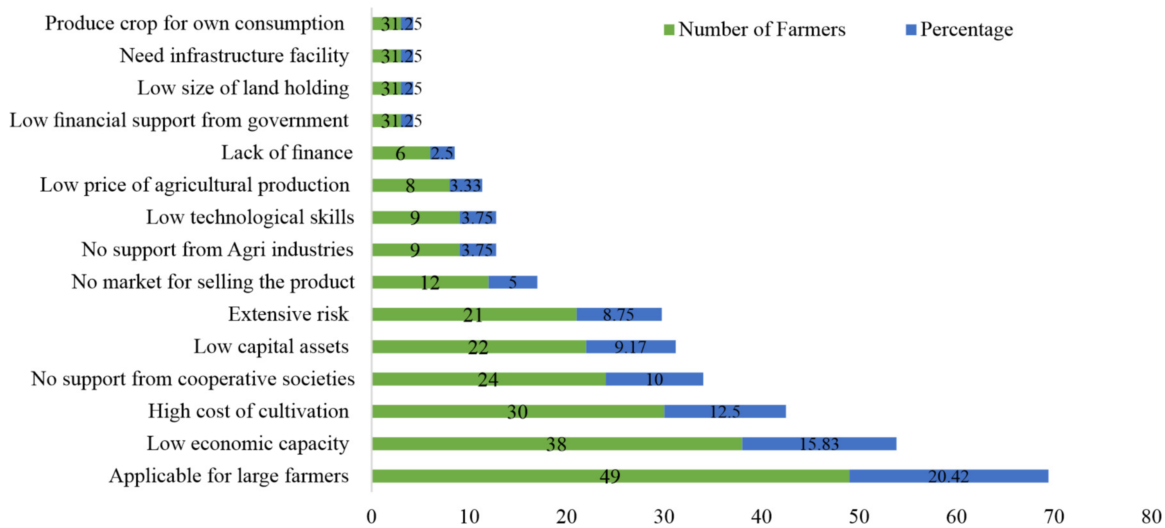

Figure 5 Farmers' limitations in using cultivation technologies

Source Based on field survey

About 20.42% farmers agreed that technologies are effective on large landholdings; therefore, small-size landholdings constitute a prime barrier. Small-scale landholders cannot afford new technologies; 15.83% of the farmers could not apply cultivation technologies. Using these technologies raised their cultivation cost, reported 12.50% of the farmers, and about 10% claimed that the support from agricultural cooperative societies and industry is not significant.

Several other barriers exist: capital assets are low; the risk involved in technologies is significant; markets are not available; the price of produce is low; farmers lack access to finance; financial support from government is low; farmers' skills are poor; and the infrastructure is inappropriate. Approximately 5% of the farmers grow food grains for their own consumption and they do not want to use cultivation technologies.

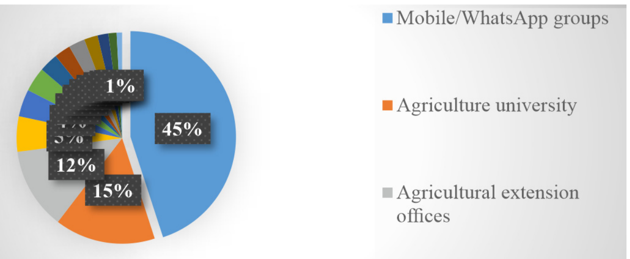

Figure 6 Agricultural input- and technology-related information providers for farmers
Source Based on field survey

Agricultural input–related information providers for farmers

Around 45% of the farmers obtain information on agricultural inputs (new technologies and varieties of seed, fertilizer, and pesticide) through mobile and WhatsApp groups (Figure 6). Therefore, social media must be used extensively to improve awareness of new technologies and other inputs.

Information and communication technologies (ICT), video, and mobile help to make agriculture cost effective (Dhehibi et al. 2020). Around 15.42% of the farmers received information on inputs from agricultural universities and 12.50% from agricultural extension offices or Krishi Vigyan Kendras (KVK). Thus, both universities and KVKs can improve farmers' awareness of various inputs. Television, local stakeholders and markets, newspapers, large landholders, relatives, and the agricultural and agri-product machine manufacturing industry were also deemed helpful in disseminating information on agricultural inputs among farmers.

Agricultural co-operative societies and KVKs created the WhatsApp groups; therefore, 65.42% of the farmers receive information from them. Most districts of Gujarat have established KVKs to provide various information to the farmers regularly. Agricultural universities also organize seminars and train farmers; therefore, around 19.17% of the farmers received information from them.

The agricultural industry and agricultural technology development industry also train farmers, but only 3.33% of farmers are beneficiaries. Shopkeepers at local markets also convey information on the latest technologies, inputs, and seeds to farmers. Relatives, large landholders, and daily newspapers were the major information providers for small farmers.

Farmers' perception of appropriate technologies and their components

It is difficult to recognize whether a technology is appropriate; therefore, this study considered farmers' opinions. About 64.17% of farmers are aware of the economic viability of technologies, 89.17% of their social viability, and 63.33% of their environmental viability, and 72% farmers know about appropriate technologies (Figure 7). The scope of using appropriate technologies in Gujarat is enormous, therefore, and agricultural development institutions should train farmers to achieve sustainable agricultural development.

Discussion on empirical results

Statistical summary of the variables

Table 3 provides the statistical summary of dependent and explanatory variables. The statistical summary includes the minimum, maximum, mean, standard

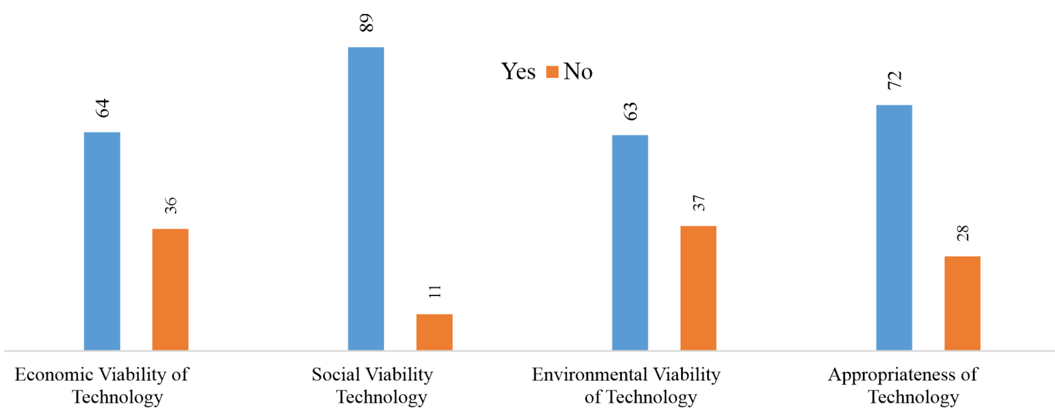

Figure 7 Farmers' awareness of appropriate technologies and their components
Source Based on field survey

Table 3 Statistical summary of variables

Variables	Min	Max	Mean	Sta. Dev.	Skewness	Kurtosis
ap	699.25	83910.56	8739.23	10097.64	3.76	23.61
ttc	250.00	2890.00	2198.55	388.89	–1.10	6.62
tal	1.00	30.00	10.34	7.61	1.07	3.33
ci	3.00	8.00	6.16	1.29	–0.34	2.20
ia	0.50	25.00	7.06	5.67	1.33	4.23
ugf	132.80	16156.35	1700.92	1950.88	3.67	22.90
ual	51.00	86.00	65.47	5.48	0.38	4.07
el	8.00	17.00	12.61	3.14	–0.09	1.66
ai	50000	720000	299679	170182	0.52	2.05
fs	2.00	12.00	5.58	1.83	1.15	4.77
ar	20.00	65.00	39.81	10.83	0.29	2.20
at	0.00	1.00	0.72	0.30	–0.51	1.91
fp	0.00	1.00	0.69	0.46	–0.83	1.69
fsg	0.00	1.00	0.44	0.50	0.25	1.06
fas	0.00	1.00	0.51	0.50	–0.05	1.00
stsf	0.00	1.00	0.32	0.47	0.77	1.59

Source Authors' estimation

Table 4 Summary results of statistical tests

Statistical test/types of models	Linear regression	Log linear regression	Nonlinear regression
Scale reliability coefficients [*Cronbach's alpha* tests]	0.6876	0.7516	0.8201
Ramsey RESET test using powers of the fitted values of agricultural production [Chi^2]	19.06*	42.12*	79.07*
Ramsey RESET test using powers of the explanatory variables [Chi^2]	8.05*	15.69*	11.34*
Akaike information criterion (*AIC*)	- 4043.965	-456.7828	- 4035.157
Bayesian information criterion (*BIC*)	- 4099.655	-401.0926	- 4125.654
Mean *VIF* for multi-correlation	2.89	4.95	62.94
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity [Chi^2]	187.75*	80.19*	169.66*
Cameron & Trivedi's decomposition of IM-test for heteroskedasticity [Chi^2]	248.87*	264.78*	284.68*

Source Authors' estimation. ** regression coefficient is significant at the 0.01 level and * regression coefficient is significant at the 0.05 level.

deviation, skewness, and kurtosis values of the corresponding variables. The values of standard deviation were found greater than 1 for most variables (except binary variables). Also, the estimates indicate the values of *skewness* were between –1 to 1 for most variables. Thus, these variables were in normal form.

Summary of statistical tests

Table 4 provides a summary of the statistical tests we used to select the appropriate model. We applied the Cronbach's alpha test, which measures the internal consistency of variables (Singh et al. 2022), to examine the internal reliability of the group of independent variables. The scale reliability coefficients for all the models were between 0 and 1; therefore, the variables have internal consistency.

The chi^2 values under the Ramsay RESET test for the fitted values of agricultural productivity and the power of explanatory variables were observed to be statistically significant at the 1% significance level, meaning that the function forms of the linear, log linear, and nonlinear regression models were found suitable to estimate the coefficient of explanatory variables with agricultural productivity. The log linear regression model provides the lower values of AIC and BIC, however, and produces better results than the linear and nonlinear regression models. In the linear and log linear regression models, the mean VIF value was reported to be less than 10. But it was 62.94 in the nonlinear regression model because the multicollinearity between the original and square terms of the explanatory variables was high.

The estimates claimed that the set of explanatory variables in the linear and log linear regression models are not multi-correlated; irrigated area has a high correlation with non-irrigated area; the economic, social, and environmental viability of technologies have a high correlation with appropriateness of technology; and gender ratio has a high correlation with family size. Therefore, we dropped non-irrigated area; economic, social, and environmental viability of technology; and the gender ratio from the regression analysis. The chi^2 values estimated under the Breusch-Pagan/Cook-Weisberg and Cameron & Trivedi's decomposition of IM-tests were detected to be statistically significant; therefore, the cross-sectional data set was not heteroscedastic.

Interpretation of regression results

We used the linear, log linear, and nonlinear regression models to estimate the regression coefficients of the explanatory variables with agricultural productivity (Table 5). The linear regression model measures the linear relationship between dependent and independent variables. The nonlinear regression model provides the nonlinearity between the output and inputs. The log linear regression model produces the elasticity of inputs with respect to output (Kumar, Sharma, and Joshi 2016; Singh, Narayanan, and Sharma 2017); hence, it is noteworthy that in these models the regression coefficients of the explanatory variables with agricultural productivity were observed to be different in sign and magnitude.

Earlier studies selected a model by the lowest values of the AIC and BIC (Singh, Narayanan, and Sharma 2017; Singh et al. 2022). The log linear regression model in this study produces the lowest values of the AIC and BIC (Table 4) and, therefore, better results than the linear and nonlinear regression models.

The *F*-values were statistically significant for all models. The estimates imply that the explanatory variables have significant variation and that the overall impact of these variables on agricultural productivity was consistent. As per the R^2 values, 99% of the variation in agricultural productivity can be explained by the undertaken explanatory variables in the proposed models. Most essential variables that have a significant impact on agricultural productivity were included in the regression models. Therefore, it is obvious that all the models produce high values of R^2.

The regression coefficient of technology cost with agricultural productivity was reported to be positive and statistically significant at the 10% significance level. The result implies that agricultural productivity increases as the application of technology in cultivation increases. A similar positive impact of technology on agricultural productivity is noted in other studies (Pingali et al. 2019; Abdullahi, Mahieddine, and Sheriff 2015).

Arable land is a vital input for agricultural production systems. Thus, the regression coefficient of total arable land with agricultural productivity was positive and statistically significant at the 1% significance level. Previous studies observe a similar positive impact of arable land on agricultural production (Xie et al. 2018; Singh et al. 2022).

The regression coefficient of cropping intensity with agricultural productivity was positive and statistically significant at the 5% significance level. This estimate implies that agricultural productivity increases as cropping intensity increases. A similar positive impact has been observed earlier (Kumar, Ahmad, and Sharma 2017). Cropping intensity helps to improve the aggregate production of food grains and cash crops. Thus, agricultural productivity is likely to increase as cropping intensity increases.

Irrigated area has a higher yielding capacity than non-irrigated area (Kumar, Sharma, and Ambrammal 2015). The regression coefficient of irrigated area with agricultural productivity was found to be positive and statistically significant at the 10% significance level. Gujarat is drought-prone (Gulati, Roy, and Hussain 2021); thus, irrigated area will be useful to increase agricultural productivity.

Agricultural labour is an important input, and it has a positive impact on agricultural productivity, but the

Table 5 Association of agricultural productivity with explanatory variables

Models	Linear Regression			Log linear Regression			Non-linear Regression		
No. of Obs.	240			240			240		
F-Value	1408.59*			1522.16*			911.49*		
R^2	0.9895			0.9903			0.9907		
Adj. R^2	0.9888			0.9896			0.9896		
Variables	Reg. Coef.	Std. Err.	P>|t|	Reg. Coef.	Std. Err.	P>|t|	Reg. Coef.	Std. Err.	P>|t|
ttc	-0.1389	0.183	0.049	0.0006	0.024	0.079	-0.1850	0.891	0.036
(*ttc*)^2	-	-	-	-	-	-	0.0000	0.000	0.053
tal	-11.3411	31.39	0.018	0.1410	0.039	0.000	114.2049	90.640	0.009
(*tal*)^2	-	-	-	-	-	-	-0.8183	2.300	0.022
ci	35.4530	55.36	0.023	0.0097	0.027	0.019	-106.2816	487.400	0.028
(*ci*)^2	-	-	-	-	-	-	13.7723	40.649	0.035
ia	16.1951	39.05	0.079	0.0078	0.026	0.063	56.6456	106.381	0.095
(*ia*)^2	-	-	-	-	-	-	-0.5522	3.576	0.077
ugf	5.1340	0.054	0.000	0.8576	0.025	0.000	4.0947	0.212	0.000
(*ugf*)^2	-	-	-	-	-	-	0.0001	0.000	0.000
ual	13.2964	12.98	0.307	0.0760	0.072	0.095	-141.6507	182.698	0.099
(*ual*)^2	-	-	-	-	-	-	1.1509	1.368	0.001
el	-34.9454	41.4	0.009	-0.0150	0.040	0.006	86.3301	246.293	0.026
(*el*)^2	-	-	-	-	-	-	-5.4981	9.925	0.080
ai	0.0005	5E-04	0.071	0.0162	0.012	0.083	0.0017	0.002	0.063
(*ai*)^2	-	-	-	-	-	-	0.0000	0.000	0.019
fs	-10.2214	41.73	0.007	-0.0013	0.021	0.052	-5.2974	196.263	0.078
(*fs*)^2	-	-	-	-	-	-	0.8212	14.481	0.055
ar	-9.9742	7.461	0.083	-0.0279	0.025	0.026	-15.3228	48.032	0.075
(*ar*)^2	-	-	-	-	-	-	0.0679	0.574	0.006
at	-13.3409	399.1	0.073	0.0026	0.032	0.036	231.2919	415.464	0.078
fp	-121.2004	162.6	0.457	-0.0141	0.014	0.305	-95.9409	167.170	0.067
fsg	74.7096	163.0	0.047	0.0041	0.014	0.077	28.8213	164.137	0.061
fas	93.6934	144.2	0.517	-0.0058	0.012	0.636	98.1618	142.427	0.491
stsf	-50.2862	173.2	0.772	-0.0070	0.015	0.639	-24.6822	176.307	0.889
Con. Coef.	14.1298	1105	0.990	1.9486	0.409	0.000	4613.3020	6489.247	0.478

Source Authors' estimation.

law of diminishing returns may render the overuse of agricultural labour unproductive (Kumar, Sharma, and Ambrammal 2015).

The application of fertilizer in cultivation improves crop yield, and the regression coefficient of fertilizer with agricultural productivity was observed to be positive and statistically significant at the 1% significant level. Farmers in the high income group can use advanced inputs and technologies to raise crop productivity (Jamal et al. 2021). When their income increases, farmers can use farm management practices and new technologies, seed varieties, organic and green fertilizers, pesticides, and irrigation instruments. As the annual income of farmers increases, agricultural productivity will improve. Therefore, the regression coefficient of the annual income of farmers with agricultural productivity was found to be positive and statistically significant at the 10% significance level.

Family size also showed a positive impact on agricultural productivity. Educated farmers have an appropriate understanding on various inputs, technologies, and proper methods of cultivation. Hence, the regression coefficient of education level of farmer with agricultural productivity was seemed positive and statistically significant at 1% significance level.

The regression coefficient of appropriate technologies with agricultural productivity was found to be positive and statistically significant at the 1% significance level. Thus, the estimate indicates that appropriate technologies have a positive impact on agricultural productivity, consistent with previous studies (Kumar, Sharma, and Ambrammal 2015; Gebeyehu 2016; Ali et al. 2017; Singh, Narayanan, and Sharma 2017; Siddick 2019; Jyoti and Singh 2020; Ashraf and Singh 2021).

Farm management practices improve as the age of farmers increase. Hence, the regression coefficient of age of respondents with agricultural productivity was positive and statistically significant at the 5% significance level. Appropriate farm management practices make agricultural development sustainable (Singh, Kumar, and Jyoti 2022).

Financial support from the government improves the economic capacity of farmers and has a positive impact on agricultural productivity. A similar positive impact has been observed earlier (Kumar, Ahmad, and Sharma 2017). The regression coefficients of, on the one hand, the farmers' financial constraints and their collaboration with agricultural universities, extension offices, co-operative societies, and industry and of sellers' skilled and technical support with, on the other, agricultural productivity were found to be statistically significant. Farmers' association with various stakeholders and with skilled and technical support have a positive impact on agricultural productivity, as has been found earlier (Desai 1994; Syan et al. 2019; Msomba, Ndaki, and Nassary 2021; Jamal et al. 2021; Singh et al. 2022).

The empirical results based on the nonlinear regression model indicate that agricultural productivity has a nonlinear and linear association with the explanatory variables. Agricultural productivity has a nonlinear relationship with technology cost, arable land, cropping intensity, irrigated area, use of agricultural labour, education level, family size, and the age of a farmer.

Agricultural productivity has a hill-shape relationship with technological development, cropping intensity, use of agricultural labour, family size, and the age of a respondent. These factors may be effective in improving agricultural productivity only to a certain extent.

Agricultural productivity has a U-shaped association with arable land, irrigated area, and the education level of a respondent and a linear association with fertilizer use and annual income. Thus, agricultural productivity increases linearly as the contribution of these factors increases.

Conclusion and policy implications

As per the empirical results, the crucial determinants of agricultural productivity are technology cost, total arable land, cropping intensity, irrigated area, use of fertilizer and agricultural labour, annual income of farmers, the use of appropriate technologies in cultivation, and financial support from government.

The descriptive results indicate that to cultivate crops, farmers were using 63 technologies with usages such as ploughing, weeding, transport, field preparation of seed planting, fertilizer application, manual seed transplanter, and water conservation.

Technological development was useful in saving water and human effort; preparing the land for planting seeds; improving seed germination, crop yield, soil quality and fertility, and the marketing process; minimizing water and fertilizer use; and reducing cultivation cost, waste material, and the negative impact of activities on ecosystem services.

Agricultural cooperative societies and extension offices, and Krishi Vigyan Kendras, disseminate information on inputs and technologies among farmers through WhatsApp groups, so farmers were conscious of the viability of technologies: 64.17% of the economic viability, 89.17% of the social viability, and 63.33% of the environmental viability.

Agricultural development institutions in Gujarat may play a key role in improving farmers' understanding of appropriate technologies and their usage in cultivation to achieve sustainable agricultural development. Farmers with small landholdings do not have the infrastructure, capital assets, economic capacity, or support from agricultural cooperative societies, industry, or government and financial institutions to invest in and use expensive agricultural technologies. The government should support the farmers financially, and policymakers should consider these issues in formulating policy for sustainable agricultural development in Gujarat. Farmers should increase their collaboration with research institutions, agricultural universities, KVKs, and local stakeholders to increase their understanding on new technologies and most useful agricultural inputs.

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