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RESEARCH NOTE

Impact of Agricultural Technologies on System Productivity: A Case Study of the Farmer FIRST Programme in Bundelkhand Region, Uttar Pradesh

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ABSTRACT

The present study assessed the effect of improved agricultural technologies disseminated under the ambitious Farmer FIRST Programme (FFP) on the system productivity of major crops in the Bundelkhand region of central India. The study used cross-sectional data from 381 farmers (167 beneficiaries and 214 non-beneficiaries) and employed Bisaliah's decomposition model to assess the impact. The findings suggest that adopting improved agricultural technologies accentuated the system productivity of adopters by around 20 per cent. The project interventions in the study region slightly increased input use level by the adopters (2.8 per cent). Still, the adoption of technologies also accentuated the input use efficiency of farmers by 24 per cent, leading to overall productivity gains. The evidence of the positive impact of adopting improved agricultural technologies in the Bundelkhand region of central India suggests that promoting similar approaches in other regions with comparable climatic and agricultural challenges can improve farm productivity and, thus, the income and livelihood of farmers.

Keywords: Technological interventions, FFP, system productivity, Bundelkhand

JEL codes: O32, Q12, Q16, Q18

I INTRODUCTION

As an agrarian economy, India has always prioritised agricultural development in its various planning periods. Past agricultural policies in the country have focused primarily on enhancing farm production and reducing hunger. However, development strategies in the sector have been reoriented in recent years in response to changing farmer needs and challenges (Choudhary et al., 2022). Transformational change in the livelihoods of farming communities has remained a major goal in the recently launched agricultural schemes and programmes. The Farmer FIRST Programme (FFP), launched by the Indian Council of Agricultural Research (ICAR), New Delhi, in 2016 with a budget of Rs. 1653.60 lakh, is designed to place farmers at the centre of agricultural development. The program aims to address their needs and challenges comprehensively to improve their livelihoods. FFP focuses on five key areas: Farm, Innovations, Resources, Science, and Technology (FIRST), and seeks to strengthen the farmer-scientist interface for participatory technology development and its application in agricultural practices (Venkatesan et al., 2023). It aims to benefit 45,000 farmers nationwide.

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The importance of such development programmes in resource-deprived areas of the country, like the Bundelkhand region, hardly needs elaboration. An uneven landscape with hard rock geology, poor soil fertility, limited groundwater availability, and unpredictable rainfall makes the region vulnerable to droughts and crop failures (Sharma et al., 2021; Singh et al., 2023). In the semi-arid tropical zone, Bundelkhand's population primarily relies on agriculture and livestock for livelihood. The Indian Grassland and Fodder Research Institute (IGFRI), based in Jhansi and under the auspices of ICAR, has been implementing the FFP in this region since 2016. Notably, an investment of Rs. 183 lakhs has been made so far to enrich knowledge and integrate improved technologies in the farmer's field of this region. Hence, its impact and ground-level success deserve the attention of policy planners and concerned stakeholders.

The majority of existing literature on impact studies has primarily focused on the effects of individual agricultural interventions, such as crop or livestock-based measures (Sharma et al., 2021; Kumar et al., 2022) or interventions related to natural resource management (Singh et al., 2024), on the welfare outcomes of farmers. However, there is a significant lack of research on the impact of comprehensive agricultural interventions in the Indian context. Furthermore, studies examining their influence on system productivity are notably scarce. Evaluating impact in terms of system productivity provides a more precise assessment of intervention effectiveness across diverse contexts. This approach facilitates evidence-based decision-making for farmers, policymakers, and stakeholders in the agricultural sector. Additionally, emphasising crop equivalent yield allows for assessing the overall efficiency and sustainability of agricultural practices, considering factors such as resource utilization efficiency and land productivity.

The current study aims to assess the impact of improved agricultural technologies on system productivity and farm income among beneficiary farmers, using the example of FFP interventions in the Jhansi district of Uttar Pradesh by the ICAR-IGFRI, Jhansi. The FFP project introduced a comprehensive range of technologies and farming practices (Table 1), including improved crop varieties, line sowing of seeds, optimal irrigation during critical growth stages and balanced fertilizer dose. This diverse approach makes it an ideal context for analyzing the impact of technology interventions on farm system productivity.

Sl no.	Technology	Description				
(1)	(2)	(3)				
1	Improved crop varieties	Wheat(RAJ-4179), Blackgram (Shekhar-2), Greengram (PDM-139 (Samrat))				
		and Groundnut (GG-2)				
2	Agronomic practices	Ploughing during summer, FYM application, vermicomposting, micronutrient application based on soil testing (ZnSO ₄ at 20-25 kg/ha), line sowing with proper seed rate, irrigation during critical crop growth stages, and integrated weed				
		management				
3.	Farm implements	Seed drill, groundnut decorticator, power-operated thresher cum grader.				
4.	Crop protection	Fungicides and biofertilizers treatment of seeds, use of biorationals				

TABLE 1. AGRICULTURAL INTERVENTIONS UNDER THE FFP

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METHODOLOGY

Study Site, Sampling Method and Data

Our study is primarily based on primary data collected from Jhansi district, located in the typical semi-arid region of Bundelkhand, Uttar Pradesh. Approximately 90 per cent of the district's annual rainfall (850-900 mm) occurs between June and September (the kharif season), with the remaining 10 per cent distributed from October to May (Choudhary et al., 2022).

For this study, we purposively selected five villages—*Pali, Palinda, Datanagar, Dhimarpura, and Parbai*—as treated villages where all project activities were implemented. In addition, five adjacent villages—*Dhikoli, Nayakheda, Ganeshgarh, Ramgarh, and Kanchanpur*—were randomly chosen as control villages. These control villages share similar agro-climatic conditions, infrastructure, and socio-economic characteristics with the treated villages. This selection criterion is strongly supported by existing literature for its effectiveness in minimizing spillover bias (Marwa et al., 2020; Singh et al., 2023).

Household heads in each village were categorized by land size, and a probability proportional to size technique was used to select households from each land size category. A total of 167 farmers from the treated villages and 214 from the control villages were chosen for the study. Primary data on the cost of cultivation and production of key crops in the study area for 2022-23 were collected using a well-designed and pretested interview schedule.

System Productivity and Yield Response

The four major crops in the selected villages were wheat, groundnut, black gram, and green gram, which accounted for approximately 82 per cent of the total gross cropped area (GCA). Farm system productivity, measured in terms of wheat equivalent yield (WEY), was calculated for each household using the following formula (Eq. 1):

WEY =
$$Yw + Ybg\left(\frac{Pbg}{Pw}\right) + Ygn\left(\frac{Pgn}{Pw}\right) + Ygg\left(\frac{Pgg}{Pw}\right)$$
 (1)

Where, Yw, Ybg,Ygn and Ygg are yield (kg per ha) of wheat, blackgram, groundnut and green gram, respectively. The terms Pw, Pbg, Pgn and Pgg denote the farm harvest prices (Rs.per kg) of these four major crops in Jhansi district, respectively.

Crop yield is determined by exogenous factors such as seeds, labour inputs (bullock, machine, and human labour), fertilizer, agrochemicals, and farmyard manure (FYM) (Singh et al., 2021). To estimate the yield response, a model within the Cobb-Douglas framework was developed (Eq. 2),

$$WEY = AS^{a1}B^{a2}M^{a3}H^{a4}F^{a5}Ac^{a6}FYM^{a7}e_i \qquad (2)$$

Where WEY represents the wheat equivalent yield (kg per ha), A denotes the scale parameter, S represents seeds, and B, M, and H indicate bullock, machine, and human labour, respectively. F refers to fertilizer, Ac stands for agrochemicals, a_i represents the output elasticity of the ith input (i = 1, 2, ..., 7), and e_i is the error term with zero mean and constant variance.

Technology Impact Assessment

Empirical studies investigating the causal impact of technological interventions present an empirical challenge when examining the outcomes and their counterfactuals within the same farmer. In other words, it is necessary to determine the impact if farmers had not adopted these technologies (Marasas et al., 2003). To address this challenge, we conducted separate estimations for adopters (Equation 3), non-adopters (Equation 4), and the pooled data (Equation 5), all represented in a log-linear form.

$$\gamma_6 LnAc_{ip} + \gamma_7 LnFYM_{ip} + \gamma_8 D + w_{ip} \qquad \dots (5)$$

Where, α_0 , β_0 and γ_0 are intercept coefficients; α_j , β_j and γ_j are elasticity parameters of jth inputs (as specified in Eq. 2), and *i* represents the number of observations (167 for the treated sample, 214 for the control sample and 381 for the pooled sample). D is the intercept dummy variable (D = 1 for treated households and 0 otherwise). Our model did not consider multicollinearity, as the estimated Variance Inflation Factors (VIF) of 3 was well below the critical threshold of 10 (Gujarati, 1995).

Further, following Greene (2000), homogeneity between the regression coefficients of equations (3) and (4) was checked by Chow's test (Eq. 6);

$$F = \frac{\binom{(RSS_p - (RSS_a + RSS_{na}))}{K}}{\binom{(RSS_a + RSS_{na})}{(N_a + N_{na} - 2K)}} \dots \dots (6)$$

Where, RSS_p indicates the residual sum of squares obtained (Eq 5), RSS_a and RSS_{na} are the residual sum of squares from the regression equations for adopters (Eq 3) and non-adopters (Eq 4), respectively. N_a and N_{na} denotes sample sizes of adopters and non-adopters groups, respectively, and K is the number of parameters to be estimated. The null hypothesis, which asserts that the parameters in the separate regressions for adopters and non-adopters are identical, is rejected if the computed F-value exceeds the critical F statistic.

Decomposition Model for Estimating Contribution of the Technology

Bisaliah decomposition model (Bisaliah, 1977) was used to determine the respective contributions of technological interventions and variations in resource use to the overall productivity gap between adopters and their non-adopter counterparts. The decomposition model is formulated by subtracting equation 3 from equation 4 and making a few algebraic adjustments, as follows:

$$Ln\left(\frac{Y_{a}}{Y_{na}}\right) = \left[Ln\left(\frac{\alpha_{0}}{\beta_{0}}\right)\right] + \left[LnS_{na}(\alpha_{1} - \beta_{1}) + LnB_{na}(\alpha_{2} - \beta_{2}) + LnM_{na}(\alpha_{3} - \beta_{3}) + LnH_{na}(\alpha_{4} - \beta_{4}) + LnF_{na}(\alpha_{5} - \beta_{5}) + LnAc_{na}(\alpha_{6} - \beta_{6}) + LnFYM_{na}(\alpha_{7} - \beta_{7})\right] + \left[\alpha_{1}Ln\left(\frac{S_{a}}{S_{na}}\right) + \alpha_{2}Ln\left(\frac{B_{a}}{B_{na}}\right) + \alpha_{3}Ln\left(\frac{M_{a}}{M_{na}}\right) + \alpha_{4}Ln\left(\frac{H_{a}}{H_{na}}\right) + \alpha_{5}Ln\left(\frac{F_{a}}{F_{na}}\right) + \alpha_{6}Ln\left(\frac{Ac_{a}}{Ac_{na}}\right) + \alpha_{7}Ln\left(\frac{FYM_{a}}{FYM_{na}}\right)\right] + \left[\varepsilon_{a} - u_{na}\right] \dots (7)$$

Where the expression $Ln\left(\frac{Y_a}{Y_{na}}\right)$ is a measure of the change in system productivity in percentage terms, $Ln\left(\frac{\alpha_0}{\beta_0}\right)$ indicating the percentage change in output due to a shift in the intercept term of the production function (neutral technological gap). The second bracketed term on the right-hand side of equation 8 measures output change due to shifts in the slope parameters of the production function (non-neutral technological gap). The sum of the neutral and non-neutral technological gaps estimates the impact on system productivity. Output change due to differences in intensity of input use is given by the third bracketed term on the right side of the equation. The subscripts 'a' and 'na' represent the adopter and non-adopters categories. Such spatial econometric analysis is important for understanding the impact of improved technologies on agricultural productivity.

III RESULTS AND DISCUSSION

System Productivity and Input Use Estimates

Farmers in the treated villages (adopters) use significantly lower inputs like seeds, fertilizers, and agrochemicals than non-adopter households (Table 2). This suggests that adopters are more efficient in using these inputs, likely due to adopting improved agricultural practices and technologies. In contrast, adopters use considerably more farm yard manure (FYM) and compost, which are organic inputs that enhance soil health and contribute to sustainable farming practices. Adhering to recommended technological practices, including high-quality seed materials, adopters increase the effectiveness of their cultivation practices and optimize the use of other inputs. Training in the operation of seed drills, threshers, graders, and groundnut decorticators, as detailed in Table 1, supports farmers in transitioning from manual labour to mechanized farming. This shift enhances efficiency and significantly reduces the time spent on labour-intensive tasks. Consequently, farmers who adopt these

technologies can pursue additional income-generating activities, ultimately increasing overall incomes for farming families.

Inputs	Overall	Adopters	Non-Adopters	Percentage difference
		(A)	(NA)	(A - NA)
(1)	(2)	(3)	(4)	(5)
Seed (kg ha ⁻¹)	47.36	43.13*	50.07	-16.09*
Bullock labour (days)	0.619	0.579	0.670	-15.72
Machine labour (hours)	9.43	11.31*	7.19	36.43*
Human labour (man-days)	14.22	10.21*	17.78	-74.14*
Fertilizer NPK (kg)	51.21	47.31**	55.81	-17.97*
Agrochemicals (litre)	0.46	0.33*	0.51	-54.55*
Farm Yard Manure (ton)	1.01	1.36*	0.89	34.56*
WEY (kg)	11131.20	12830.38*	10602.25	17.37*
Sample size	381	167	214	

TABLE 2. GEOMETRIC MEAN LEVELS OF SYSTEM PRODUCTIVITY AND INPUT USE

Note: SWEY: System wheat equivalent yield; *p<0.01, **p<0.05

It is important to note that the WEY is significantly higher for adopter farmers, indicating the sustainability of crop farming in the project villages. Additionally, adopter households experienced 1.19 per cent lower system cultivation costs, while their returns per rupee of investment were 25 per cent higher than those of non-adopter farm households. The cost-reducing benefits of adopting improved agricultural practices have also been observed by Choudhary et al. (2022), and the findings regarding yield and income benefits from adopting improved farming practices align with those of Rao et al. (2017).

Category	WEY (kg	System cost of	System gross	System netreturn	Returns per
	ha ⁻¹)	cultivation	return	(Rs ha ⁻¹)	rupee of
		(Rsha ⁻¹)	(Rsha ⁻¹)		investment
(1)	(2)	(3)	(4)	(5)	(6)
Adopters	12830.38	81346.87	121241.57	39894.70	1.49
Non-Adopters	10602.25	82331.64	98237.30	15905.66	1.19
Relative difference	21.01	-1.19	2.34	150.82	24.91
(Per cent)					

TABLE 3. COMPARATIVE FARM HOUSEHOLD ECONOMICS: ADOPTERS vs NON-ADOPTERS

Source: Authors' estimates based on survey data

Production Function Estimates

The results of Chow's test are presented in Table 4. The test rejects the null hypothesis of homogeneity of the regression coefficients for the two production functions (Equations 3 and 4), indicating that there is significant evidence of a structural change in the production relationships between farmers in the treated and control villages, likely as a result of the project interventions. In other words, the effect of the interventions on productivity is not uniform across all farmers; the treated and control groups exhibit different production behaviours. Hence, it is more appropriate to estimate separate regression lines for adopters and non-adopters, as this approach accounts for the differences in production dynamics between the two groups. Using

separate regressions provides a better fit to the data than a pooled regression model (Equation 5), which would assume that the production relationships are the same for both groups and, therefore, fail to capture the structural changes introduced by the interventions. This finding underscores the importance of accounting for these differences when analyzing the impacts of agricultural interventions, as a pooled approach would obscure key variations in productivity across different farmer groups.

TABLE 4. CHOW'S TEST ANALYSIS OF PRODUCTION FUNCTION DISPARITIES				
Category	Ν	Df	Residual sum of squares (RSS)	Chow's F-stat
(1)	(2)	(3)	(4)	(5)
Adopters	167	159	237.16	10.44*
Non-adopters	214	206	117.29	
Pooled	381	372	435.57	
*p<0.01				

Table 5 presents the estimated output elasticities for our sampled categories: adopters, non-adopters, and the pooled sample. The coefficients for seed, labour (both machine and human), fertilizer, and FYM clearly show a significant positive impact on all production relationships. The production elasticities, being less than one, suggest diminishing marginal productivity for each input, implying that resource use is within the optimal range for the production stages. Notably, adopters show higher seed, fertilizer, machine labour, and FYM elasticities. The lower elasticity of human labour among adopters may be due to the potential overutilization of manpower in the treated villages.

TABLE 5. ESTIMATES OF OUTPUT ELASTICITIES

Inputs	Pooled	Non-Adopter	Adopter
(1)	(2)	(3)	(4)
Intercept	2.31*	1.51*	2.03*
Seed (kg ha ⁻¹)	0.09*	0.07*	0.13*
Bullock labour (days ha ⁻¹)	0.05	0.03	0.09
Machine labour (hrs ha ⁻¹)	0.07*	0.08*	0.11*
Human labour (mandays ha ⁻¹)	0.13*	0.17*	0.14*
Fertilizer NPK (kg ha ⁻¹)	0.15*	0.19**	0.09*
Agrochemicals (litre ha ⁻¹)	0.09**	0.07	0.10**
Farm Yard Manure (t ha ⁻¹)	0.15*	0.09*	0.19*
Dummy	-0.19	-	-
Adjusted R ²	0.78	0.81	0.83
F-Statistics	6.24*	7.32*	6.48*
Sample size	381	167	214

*p<0.01, **p<0.05

Estimates of Decomposition Model

Following the confirmation of a structural check in the production relationships through the Chow test, the overall change in system productivity was assessed using the decomposed model (Eq. 7). The estimated productivity increase for adopters

compared to non-adopters was 19.36 per cent (Table 6), marginally low than the observed difference of 21.01 per cent. This slight discrepancy of 1.65 per cent is attributed to random error, common in empirical research and considered insignificant. This suggests that the decomposition model used in the study fits well and accurately reflects the farming conditions in the study area. The analysis also identified two key components that influenced productivity changes: the neutral technological component and the non-neutral technological change. The neutral technological component, which refers to technologies that do not directly enhance productivity, had a negative impact on the productivity difference, reducing productivity by 7.33 per cent. On the other hand, non-neutral technological change, which involves technologies explicitly designed to improve productivity, had a positive effect of 23.89 per cent. These findings emphasize the importance of adopting technologies directly linked to productivity improvement. The study's results are consistent with those of Mondal et al. (2012), who also found negative impacts from neutral technological components in the Bundelkhand region of Madhya Pradesh. This reinforces the idea that while technology adoption can boost productivity, the effectiveness of the technologies largely depends on their direct relevance to improving agricultural output.

TABLE 6. DECOMPOSITION OF SYSTEM PRODUCTIVITY DIFFERENCES					
S.No.	Productivity difference and its sources	Percentage share			
		Sub-total	Total		
(1)	(2)	(3)	(4)		
Ι	Total observed difference		21.01		
II	Technology difference		16.56		
	1. Neutral technological gap	-7.33			
	2. Non-neutral technological gap	23.89			
	a) Seeds	10.43			
	b) NPK fertilizer	8.23			
	c) FYM	10.21			
	d) Agrochemicals	-2.65			
	e) Bullock labour	-7.21			
	f) Machine labour	11.21			
	g) Human labour	-6.33			
III	Due to relative change in input use level		2.79		
	a) Seeds	-1.89			
	b) NPK fertilizer	-4.71			
	c) FYM	11.21			
	d) Agrochemicals	-3.41			
	e) Bullock labour	1.01			
	f) Machine labour	3.31			
	g) Human labour	-2.72			
IV	Total estimated difference		19.36		

The positive contribution of non-neutral technological change also suggests that farmers in the control villages could have experienced a productivity increase of approximately 24 per cent if they had adopted improved technologies while keeping input use efficiency constant. Moreover, technological adoption led to increased efficiency in the use of seeds (10.43 per cent), fertilizer (8.23 per cent), farm yard manure (FYM) (10.21 per cent), and machine labour (11.21 per cent). This indicates

that adopting better technologies not only directly improves productivity but also optimizes the use of resources on the farm.

The study also examined the impact of input use levels on productivity differences between adopters and non-adopters, and it was found that non-adopters could increase their farm productivity by 2.79 per cent if they used inputs at the same levels as adopters. Among adopters, greater utilization of FYM and machine labour contributed to yield gains of 10.21 per cent and 11.21 per cent, respectively. These findings align with previous research, such as studies by Chatterjee et al. (2020) and Kumar et al. (2021), emphasising the positive contribution of complementary inputs to improving agricultural productivity. Overall, the findings underscore the importance of technological adoption and efficient input utilization in enhancing farm productivity.

IV

CONCLUSION AND POLICY IMPLICATIONS

The findings of the study suggest that sensitizing farmers to use improved farming technologies and practices can have an encouraging effect on the system productivity of their farms. Nonetheless, the project interventions in the study region slightly increased the input use level by the adopters (2.79 per cent). Still, the adoption of technologies also accentuated the input use efficiency of farmers by 24 per cent, leading to overall productivity gains. The evidence of the positive impact of adopting improved agricultural technologies from the Bundelkhand part of India highlights the potential for similar approaches to be implemented in other regions facing similar climatic and agricultural challenges.

Policy efforts should prioritize spreading farmer-centric technologies through targeted extension services and training programs. Emphasis should be placed on promoting quality seeds, mechanized farming techniques, and efficient input management. Mechanization reduces labour demands and allows farmers to diversify into additional income-generating activities, thereby bolstering household incomes and resilience against risks. Addressing barriers to technology adoption, such as improving access to finance for machinery purchases and ensuring reliable supply chains for inputs like fertilizers and seeds, must be a key policy focus. Strengthening monitoring and evaluation frameworks is crucial to continuously assess the impact of technological interventions on productivity and input efficiency, thereby supporting sustainable agricultural development nationwide. Aligning policies with these principles can facilitate a transformative shift towards sustainable agriculture and improved livelihoods across India.

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REFERENCES

- Bisaliah, S. (1977). Decomposition analysis of output change under new production technology in wheat farming: Some implications to returns on research investment, *Indian Journal of Agricultural Economics*, 32(3), 193-201.
- Chatterjee, S., Chakraborty, R., and Banerjee, H. (2020). Economic impact assessment of conservation agriculture on small and marginal farm households in eastern India. *Agricultural Economics Research Review*, 33,127–138.
 Choudhary, B.B., I. Dev, P. Singh, R. Singh, P. Sharma, K. Chand, K.K. Garg, K.H. Anantha, V. Akuraju, S. Dixit, S.
- Kumar, A. Ramand N. Kumar (2022). Impact of soil and water conservation measures on farm productivity and income in the semi-arid tropics of Bundelkhand, central India, *Environmental Conservation*, 49, 263-271.
- Choudhary, B.B., P. Sharma, M. Choudhary, S. Kumar, R.P. Dwivedi, H.S. Mahesha, S.K. Singh and S.K. Dubey (2022). Does adoption of improved agricultural practices reduce production costs? Empirical evidence from Bundelkhand region, Uttar Pradesh, India. *Current Science*, 123(10), 1232-1236.
- Greene, W. H. (2000). Econometric analysis (Fourth ed.). Prentice-Hall International.
- Gujarati, D.N. (1995). Basic econometrics, 3rd ed., McGraw-Hill.
- Kumar, S., P. Sharma, Satyapriya, P. Govindasamy, M. Singh, S. Kumar, H.M. Halli, B.B. Choudharyand M. Bagavathiannan (2022). Economic impression of on-farm research for sustainable crop production, milk yield, and livelihood options in semi-arid regions of central India, *Agronomy Journal*, 114(3), 1769-81.
- Marasas, C.N., M. Smale and R.P. Singh (2003). The economic impact of productivity maintenance research: Breeding for leaf rust resistance in modern wheat, *Agricultural Economics*, 29(3), 253–263.
- Marwa, M.E., J. Mburu, R. Elizaphan, J. Oburu, O. Mwai and S.Kahumbu (2020). Impact of ICT based extension services on dairy production and household welfare: the case of iCow service in Kenya, *Journal of Agricultural Sciences*, 12(3), 1–12.
- Mondal, B., A. Singhand I. Sekar (2012). Impact of watershed development programmes on crop productivity: A decomposition analysis, *Indian Research Journal of Extension Education*, 2, 234–238.
- Rao, C.A.R., B.M.K. Raju, J. Samuel, R. Dupdal, P.S. Reddy, D.Y. Reddy, E. Ravindranath, M. Rajeshwarand C.S. Rao (2017), Economic analysis of farming systems: Capturing the systemic aspects, *Agricultural Economics Research Review*, 30(1), 37–45.
- Sharma, P., B.B. Choudhary, P. Singh, S. Kumar, G. Gupta and I. Dev (2021). Can forage technologies transform Indian livestock sector? Evidences from smallholder dairy farmers in Bundelkhand region of central India, *Agricultural Economics Research Review*, 34 (Conference Number), 73-82.
- Singh, P., M. Goyal, and B.B. Choudhary (2021). Drivers of foodgrain productivity in Uttar Pradesh: Panel data analysis, Economic and Political Weekly, 38, 40–45.
- Singh, P., B.B. Choudhary., R.P. Dwivedi., A. Arunachalam., S. Kumar and I. Dev (2023). Agroforestry improves food security and reduces income variability in semi-arid tropics of central India, Agroforestry System, 97, 509-518.
- Singh, P., B.B. Choudhary, P. Sharma, S. Kumar, I. Dev., R. Singh, K. K. Garg, K. Chand., A. Ram., N. Kumar and A Arunachalam (2024). Impacts of soil and water conservation measures on farm technical efficiency in the semi-arid tropics of central India, *Environmental Conservation*, 1-8. doi: 10.1017/S0376892924000146
- Venkatesan, P., N. Sivaramane, B.S. Sontakki, C.S. Rao, V.P. Chahal, A.K. Singh, P.S. Sivakumar, P. Seetharaman and B. Kalyani (2023). Aligning agricultural research and extension for sustainable development goals in India: a case of farmer FIRST programme, *Sustainability*, 15(2463), 1-15.