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Agro-Technological Innovation and Cultivable Waste as Drivers of Agricultural Value Added: Empirical Evidence from Khyber Pakhtunkhwa, Pakistan

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ABSTRACT

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Background: Technological innovation and efficient land use are important to improve agricultural productivity in agrarian based economies. However, the precise impact of agro-technological innovation and cultivable waste on agricultural performance in Khyber Pakhtunkhwa has not yet been specified.

Objective: This study explored the effects of agro-technological innovation and cultivable waste on agricultural output in Khyber Pakhtunkhwa.

Methodology: The data for this study are annual time series from 2005 to 2022, and the model is a vector autoregressive (VAR) model that captures the dynamic interrelationships among the variables. The augmented Dickey-Fuller (ADF) test was used to test stationarity, and variance decomposition and Granger causality were applied to reveal directional correlations. An autoregressive distributed lag (ARDL) model was used to conduct robustness tests for mixed orders of integration.

Results: Technological innovation had a positive and statistically significant effect on agricultural production. In contrast, cultivable waste is inversely or strongly linked to agricultural outcomes, but has an indirect effect on technological innovation, indicating that agricultural output is relatively persistent, primarily because of lagged values. The results of the Granger causality also support the existence of a bidirectional relationship between innovation and output, implying a feedback mechanism.

Conclusion: Technological innovation is a backbone factor that contributing to agricultural development in Khyber Pakhtunkhwa. To sustainably increase productivity, technology must be adopted more quickly, which implies spending more on and using the infrastructure more efficiently.

Plain Language Summary

This research emphasizes the contribution of modern agricultural technologies and cultivable waste to productivity in Khyber Pakhtunkhwa, Pakistan, using annual time series data from 2005 to 2022. The findings reveal that the application of modern

technologies, such as better machines and farming methods, significantly boosts agricultural production; however, the reuse of previously cultivated land does not directly boost productivity or a mutually reinforcing relationship that boosts agricultural outcomes and encourages spending in the agro-technological sector. These results suggest that simply increasing farmland is insufficient for sustaining productivity growth. Agricultural development is crucial to the successful adoption of technology and efficient resource management. Policymakers must focus on providing better access to modern tools, and training programs for farmers, and improving the agricultural infrastructure to enable sustainable growth.

Introduction

In developing countries with predominantly agrarian economies, agricultural development increasingly depends on technological advances and the efficient use of available resources. Although the agricultural sector plays an important role in the livelihoods and economic stability of the region in KP, improvements in agricultural productivity have not been consistent over time. Even though the importance of cultivable waste (unused but productive land) increased significantly due to the use of modern agricultural technology (mechanization, precision agriculture, and better agricultural inputs), there has been limited empirical research on cultivable waste (Rana et al., 2022; Ahmed et al., 2024).

Technological innovation plays a key role in agricultural development. Advances in farm technology, including effective irrigation systems, genetically improved seed varieties, and GPS-enabled machinery, along with better information and input management, have led to significant increases in productivity and resource use (Fuglie, 2018; Barrett et al., 2022). However, these advancements can affect emerging economies only if they are able to adapt and have efficient institutions and infrastructure (Gyamfi et al., 2024; Aijaz et al., 2025). At the same time, inadequate land management prevails, restricting farming production, particularly in areas where productive land is not being utilized due to economic, institutional, and environmental issues. (Nkonya et al., 2015; Deininger and Goyal, 2025).

Recent advances in smart agriculture, such as artificial intelligence (AI), Internet of Things (IoT), and precision farming technologies, have opened new opportunities to improve agricultural productivity (Maffezzoli et al. 2022; Aijaz et al. 2025). These innovations are not adopted to a high level, however, due to financial constraints, limited agricultural extension services, and technical competency among farmers (Barrett et al., 2020; Barrett et al., 2022). While the need exists to utilize vacant cultivable land for higher productivity, there are no empirical study on the relationship between vacant cultivable land and technological innovation (Ahmed et al., 2025; Babu et al., 2026).

This study offers first of its kind evidence on the dynamics of agro-technological innovation and the cultivable waste in KP, adding to the literature.

First, the dynamic relationship between these variables is considered, and second, the effect of these variables is evaluated in the short- and long-term in an appropriate econometric approach.

Methodology

Sources of Data

Annual time-series data were obtained from the Pakistan Bureau of Statistics (PBS), Agriculture Extension Department, World Bank and Khyber Pakhtunkhwa (KPKH) Bureau of Statistics.

Variables of Study

Value added in agriculture was taken as dependent variable (Agricultural value added (AVD)). The amount of agricultural machinery represents agro-technological innovation (ATI) while the area of agricultural land, which is not used, represents cultivable waste (CW).

Model Specification

All variables are log transformed:

$$\ln(\text{AVD}_t) = \alpha + \beta_1 \ln(\text{ATI}_t) + \beta_2 \ln(\text{CW}_t) + \varepsilon_t \text{ ----- (Eq.1)}$$

Here, α is the intercept, and β_1 and β_2 are elasticities.

Econometric Approach

The model used in this study is vector autoregressive (VAR) model that is utilized to analyze the dynamic relationship between the variables. The augmented Dickey-Fuller (ADF) test was used for stationarity, and variance decomposition analysis has

applied to analyze the influence of each variable in the system dynamics. Furthermore, a Granger causality test was performed to decide the directionality of the variables' relationships. The variables were mixed-order integrated and to assess the robustness, the autoregressive distributed lag (ARDL) model was employed. The results need to be interpreted with caution, due to the small sample size.

Results

Time-Varying Coefficients (Vector Autoregressive Results)

The results of the vector autoregressive (VAR) reported in Table I suggested that a high persistence in agricultural value added: almost 90.94% of the variability of the present level of value added is explained by the values of itself at the previous period. This result points to very strong temporal persistence in agricultural production, while the statistical significance of the impact of technological innovation on agricultural production in the short run shows that there is a feedback relationship: there is no statistical evidence of an effect of cultivable waste on agricultural production, but there is significant evidence of an effect of technological innovation on cultivable waste; unused land may lead to adaptive technological responses in the agriculture sector.

Variance Decomposition

As can be seen from the variance decomposition analysis presented in Table II, the share of the own shocks of agricultural production explaining the variation of agricultural output is high in both the short run and the long run, indicating strong path dependence within the agricultural sector. The contribution of agro- technological innovation was gradually and slowly increasing over time, indicating slow technology diffusion and slow adoption, which implies that agro- technology, was having a limited direct effect on the productivity growth, as agro- waste contributed to agricultural production to a small extent.

Stationarity Results

The orders of integration obtained from the results of the augmented Dickey-Fuller (ADF) test presented in Table III show mixed orders of integration for the study variables. The agricultural value-added (AVD) and agro- technological innovation(ATI) will be stationary at level I(0), and the cultivable waste(CW) will be stationary after first differencing, in the sense that they would be integrated at level I(1). The estimation method of autoregressive-distributed lag (ARDL) is deemed as appropriate for the use of variables at different time periods of integration.

Granger Causality Results

The result of the Granger causality test results as shown in table IV indicates that there is a bidirectional test to agro technological innovation and agricultural value added, this means there is a reinforcing relationship between agro technological innovation and agricultural value added, while cultivable waste has only a unidirectional causal effect on agricultural value added and agro technological innovation respectively. This means that land that is idle can help spur the technological adaptation and agricultural development.

The results of Ordinary Least Squares(OLS) are provided in Table V, which shows the OLS results that agro-technological innovation has a positive and significant effect on agricultural valueadded ($p\text{-value} \leq 0.01$, $\beta=0.94$). Cultivable waste had no statistically significant direct effect on agricultural value-added. But, from previous VAR and Granger causality studies, it has been deduced that cultivable waste can have an indirect influence on agricultural performance through its impact on technological innovation. The model has good explanatory power with an R^2 value of 0.84, which means that the included variables explain a large proportion of the variation in agricultural value-added.

Discussion

The results imply that agro-technological innovation plays an important role in agricultural performance and that agricultural activities also exhibit structural rigidities and path dependency, which correspond to the high persistence of production (Fuglie, 2018; Abdullahi et al., 2024).

Adoption, learning, and adjustment processes are slow. The short-term impact of technological innovations on productivity can be small. However, the long-term impact can be significant. Low technology uptake is linked to financial constraints, poor agricultural services, and a lack of technical knowledge in developing countries.(Barrett et al.2022;Aijaz et al. 2025).However, the be-directional causal relationship between innovation and agricultural outputs has been associated with the endogenous growth theory that posits that higher productivity results in increased investments in innovation(Sarfraz et al., 2006; Pardey et al., 2023).

The indirect role of cultivable waste in agricultural development is very small. The green revolution towards underutilized land can stimulate technological innovation and adaptation, but not land expansion. Without proper irrigation, infrastructure development, and sound land management, it is unlikely that more productive land can be brought under cultivation (Nkonya et al., 2015; Deininger and Goyal, 2025).

Limitations: This study are limited and must be taken into account. A small number of annual time series, between 2005 and 2022, were used for analysis. Secondly, due to the inapplicability of well-documented evidence on agro-technological innovation, the indicators used to measure agro-technological innovation by proxy were used instead. These measurements might not be sufficiently multidimensional to assess the level of technological change in the sector. These are some factors, which were not included as data were limited such as irrigation intensity, fertilizer consumption and climatic condition etc. These limitations should be overcome by further studies, which should involve larger data sets and the additional explanatory variables that are important in the analysis but have been missing.

Policy Implications

Other policies should aim to expand credit for farm mechanisation, subsidies for agricultural technologies, and agricultural extension services. Moreover, enhanced investment in irrigation facilities and rural infrastructure is crucial to boosting productivity and promoting sustainability in agriculture. Furthermore, policymakers should focus on better utilization of land rather than mainly on the extension of cultivable land use.

Conclusion

Agro-technological innovation remains one of the significant parts of the agricultural growth of Khyber Pakhtunkhwa. But cultivable waste does not have a direct impact on productivity. Agricultural output also has a strong persistence and is closely related to the dynamics of technological innovation. The results indicate that sustainable development of agriculture relies more on technology than on the extension of cultivated areas. Policy interventions should thus prioritize speeding up the innovation uptake and improving land use efficiency by facilitating synergy in investment in infrastructure, technology, and resource management.

Future Research

Further research should explore the relationship between the growth of real estate, water scarcity, and an increase in cultivable waste, as well as the reduction in agricultural productivity. Comparative studies between different provinces, like Sindh and Balochistan, could also shed extra light on the effective integration of underutilized labour resources in a productive agricultural system.

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Table I: VAR and Variance statements and Declarations (Auto regression estimate, standard errors in () & t-statistics in [])

	LAGR_V_D	LAGR_T_I	LCULT_W
LAGR_V_D(-1)	0.909440	0.615582	-0.073966
	(0.08211)	(0.25275)	(0.12070)
	[11.0756]	[2.43554]	[-0.61278]
LAGR_T_I(-1)	0.038489	0.086003	0.272789
	(0.08644)	(0.26608)	(0.12707)
	[0.44524]	[0.32322]	[2.14671]
LCULT_W(-1)	0.085959	0.582656	0.493964
	(0.11727)	(0.36097)	(0.17238)
	[0.73301]	[1.61416]	[2.86547]
C	0.560947	2.277619	-1.711185
	(0.41313)	(1.27166)	(0.60730)
	[1.35780]	[1.79106]	[-2.81769]

Source: Authors' own calculations

Table II: Variance decomposition analysis

Variables	Period	S.E	AGR-V-D	AGR-T-I	C_W
Variance decomposition of AGR-V-D	1	0.0162	100.00	0.000	0.000
	2	0.0224	98.861	0.357	0.782
	3	0.0269	97.090	0.866	2.044
	4	0.0305	95.192	1.405	3.403

	5	0.0338	93.404	1.908	4.688
Variance decomposition of AGR-T-I	1	0.0500	3.355	96.645	0.000
	2	0.0529	7.300	86.297	6.410
	3	0.0553	10.755	80.723	8.520
	4	0.0572	13.950	76.089	9.967
	5	0.0589	16.822	72.309	10.868
Variance decomposition of C_W	1	0.0239	0.019	7.360	92.621
	2	0.0284	0.278	18.150	81.571
	3	0.0303	0.974	18.663	80.362
	4	0.0315	1.968	19.066	78.965
	5	0.0323	3.165	19.1147	77.717

Cholesky ordering: LAGR_V_D LAGR_T_I LCULT_W

Table III: Augmented Dicky-Fuller (ADF)

Variables	At I(o)	
Agriculture value added	t-statistic	Critical value
	-4.37(0.02)	1% -4.66
		5% -3.73
		10% -3.31
Agro-technological innovation	-3.77(0.047)	1% -4.67
		5% -3.733
		10%-3.31
Cultivable waste	-2.238(0.4396)	1% -4.66
		5% -3.733
		10% -3.31
Cultivable waste	First Difference I(1)	
	-4.459(0.0157)	1% -4.66
		5%-3.733
		10%-3.32

Table IV: Pairwise Granger Test (Lag1)

Null Hypothesis	Observations	F-Statistic	Prob-value
Granger-cause	17	11.1555	0.0049

		3.11672	0.0993
		5.24110	0.0381
CULT_W does not Granger-cause AGR-V-D	17		
AGR-V-D does not Granger-cause CULT_W		0.69725	0.4177
		7.57320	0.0156
CULT_W does not Granger-cause AGR_T_I	17		
AGR_T_I does not Granger-cause CULT_W		0.10189	0.7543

Source: Authors' own calculations

Table V: Regression Analysis (Dependent Variable: AGR_V_D)

Variables	Coefficient	SD Error	t-statistic	Prob-value
C	2252	1.293853	0.929203	0.3675
AGR_T_I	0.939210	0.142119	6.608615	0.000
CULT_W	0.322286	0.379627	0.848954	0.4093
R ²		0.840011	Mean dependent var	10.143
Adjusted R ²		0.818680	S.D. dependent var	0.1269
Standard. Error of regression		0.054051	Akaike info criterion	-2.8468
Sum squared resid		0.043823	ScSchwarz criterion	-2.6984
Log likelihood		28.62084	Hannan-Quinn criterion	-2.8263
F-statistic		39.37835	Durbin-Watson stat	1.1763
Prob(F-statistic)		0.000001		

Source: Author's own calculations



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