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Smart ML Integration for Sustainable Food Security: A Driscoll-Kraay Approach

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Abstract

This study empirically examines the impact of smart ML integration on sustainable food production in six South Asian countries from 2000 to 2022 using Driscoll-Kraay fixed-effects regression. The main findings reveal that mobile cellular subscriptions (ln_ICT), representing smart ML integration, exert a positive and statistically significant impact on sustainable food production, confirming that digital connectivity serves as a critical enabler for smallholder productivity through real-time data access, weather forecasts, market information, and agricultural extension services. Water stress index (ln_WSI) exhibits a positive and significant effect, indicating adaptive efficiency whereby resource-constrained regions adopt innovative water management technologies rather than functioning purely as a production constraint. Agricultural employment (ln_EG) shows a negative but insignificant coefficient, aligning with structural transformation literature documenting labor shifts from agriculture to industry and services. Among control variables, agricultural productivity index (ln_API) yields a negative insignificant coefficient, clean energy (ln_CE) exhibits a positive insignificant effect, and agriculture value added (ln_AF) demonstrates a positive insignificant coefficient, suggesting these channels require longer time horizons or enabling institutional frameworks to materialize in the South Asian context. The model explains approximately 72 percent of within-country variation in food production outcomes. Policy recommendations include expanding rural mobile broadband infrastructure, scaling water-efficient technologies, and strengthening regional cooperation on transboundary water management.

Keywords: Smart ML integration, sustainable food production, water stress, South Asia

JEL Classification Codes: G21, G23, O33

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1. Introduction

The digital transformation, value creation mechanism and sustainable food security are all key components of modern agriculture and economic development. Food security is the ability of all people always to access enough food to maintain a healthy and active lifestyle in line with their culture and dietary habits continues to be one of the most urgent issues of the twenty-first century (Peng & Berry, 2019). Despite significant improvements in agriculture and food production system, in 2022, some 735 million people were hungry, and climate change, geopolitical conflicts, disrupted food supplies, and economic contraction following the pandemic exacerbated the situation (Johnson, 2024; Vahdanjoo et al., 2025). Therefore, conventional methods of food security which aim at improving volume via more inputs and land have been insufficient in tackling the multi-facet of the problem of availability, access, utilization and stability.

In this scenario, DT could be considered as a potential roadmap to re-imagine food systems. Smart integration of machine learning (ML) technologies, especially the Internet of Things (IoT), has been identified as a pivotal enabling factor, allowing physical machines to be linked together, real-time data to be collected, and automatic responses to be made to various situation changes in the farm (Mohsin et al., 2025). Examples of IoT in agriculture are soil moisture sensors, weather prediction systems, pest identification and monitoring, livestock tracking, automated irrigation systems, precision fertilization, and traceability of the supply chain (Villa-Henriksen et al., 2020). These technologies allow the farmers to use the inputs optimally, prevent wastage, and increase the output, such as water, fertilizers, and pesticides (Khanna & Kaur, 2019). Moreover, real-time crop health monitoring and early detection of disease prevents post-harvest loss and ensures quality harvest. Mobile connectivity is an essential enabler for smallholder farmers, offering services like weather forecasts, market prices and pest warnings, as well as extension services (Tzounis et al., 2017); fixed broadband provides bandwidth and reliability that is essential to advanced ML-based use-cases such as automated irrigation, supply chain tracking and data-intensive precision agriculture (Pfeiffer et al., 2021).

But conscious value creation processes need to turn digital technologies into real food security gains. Value creation is the mechanism by which technology inputs translate into economic, social and environmental returns for food system actors – farmers, processors, distributors, retailers and consumers (Vahdanjoo et al., 2025). These mechanisms are realized through various channels,

such as a reduction in information asymmetries, the optimization of production costs, minimization of post-harvest losses, improved quality and safety through traceability and the possibility of price discovery through digital markets (Mühl et al., 2025). These benefits are crucial to be in line with the sustainability imperatives, and productivity gains should not come at the cost of natural capital loss or environmental systems' degradation (Shao & Marwa, 2025). This holistic approach places smart ML integration in the role of decreasing transaction costs and improving coordination and information flows in all four dimensions of food security (El Bilali & Allahyari, 2018). This study, therefore, explores the direct and indirect effects of the integration of smart ML and value creation on the sustainable food security outcomes and pinpoints the priority factors for policy making and investment planning in the context of South Asia.

Primary Question

Does smart ML integration via mobile connectivity enhance sustainable food production in South Asia?

Secondary Questions

1. Does water stress be a constraint or a driver of adaptive innovation for sustainable food production?
2. Does agricultural employment help or hinder sustainable food production amid structural transformation?
3. Do renewable energy and industrial-agricultural linkages independently drive sustainable food production outcomes?

2. Literature Review

2.1 Digital Transformation, Smart ML Integration, and Value Creation

The digital revolution of agriculture has significantly taken off, and smart integration of machine learning (ML) has become a game-changer in achieving food security sustainably. The Internet of Things (IoT) is a concept that brings together devices, sensors and communication infrastructure to gather data and act based on it without the need for human intervention (Villa-Henriksen et al., 2020). Some of the IoT applications are soil moisture monitoring, weather prediction, pest

monitoring, automatic irrigation and supply chain tracking (Khanna & Kaur, 2019). These technologies allow farmers to manage and optimise their inputs, such as water, fertilizers, and pesticides, while enhancing their crop yields (Jayalath et al., 2025). Mobile connectivity provides information to smallholder farmers such as weather, market prices and extension services, thereby reducing information gaps in rural areas (Tzounis et al., 2017). Fixed broadband has the characteristics that are necessary to enable advanced ML applications like real-time supply chain tracking and data-intensive precision agriculture.

But intentional value creation processes need to be put in place to convert digital technologies into food security gains. Value creation provides economic, social and environmental returns to the food system actors (Vahdanjoo et al., 2025). The work is followed by lowering information asymmetries, decreasing the post-harvest losses which account for 30 to 40% of the losses in developing nations and enhancing the product quality with traceability, and facilitating price transparency (Annapure et al., 2022; Mühl et al., 2025). Importantly, the increases in productivity should not compromise the natural capital (Shao & Marwa, 2025). This holistic approach puts value creation as the key enabling process between the integration of smart ML and the four pillars of food security: availability, access, utilization, and stability (El Bilali & Allahyari, 2018).

2.2 Resource Nexus, Industrialization, and Macroeconomic Factors

Agriculture is responsible for 25% of the global greenhouse gas (GHG) emissions, and 70% of freshwater withdrawals (Litskas et al., 2020). The water-energy-food nexus reveals key linkages such as the impact of water stress on production, the role of energy in pumping water, and that food production is reliant on both (Li et al., 2019). Clean energy transition decreases the carbon footprint of the food systems and lowers the energy costs. Industrial development promotes food production by providing inputs for agriculture, value addition and storage facilities (cold chains) (Annapure et al., 2022;Szarek, 2025). Market linkages can help farmers to value-add primary produce which gives them more opportunities. The macroeconomic aspects are also significant: inflation lowers the purchasing power of all households, especially the poorest (Kidane & Woldemichael, 2020); GDP growth generate space for investing in infrastructure (Tamasiga et al., 2025). However, Kadiri et al., (2025) show that pro-poor growth, which focuses on the smallholder farmers, is more effective in delivering food security growth compared to growth geared towards urban sectors.

2.3 The South Asian Context and Research Gaps

South Asia (Bangladesh, Bhutan, India, Nepal, Pakistan and Sri Lanka) is home to 25% of the world's population and suffers from a chronic issue of food insecurity and productivity gaps in agriculture (Farrukh et al., 2020). The main challenges are the high population density, transboundary water conflicts, the low level of digitalization in rural areas, and the regular climate shocks (Khalid, 2020). Agricultural practices are from intensive rice–wheat farming to subsistence farming (Kaur, 2021). Digital infrastructure has been expanding very quickly, while fixed broadband has been focused in the urban areas (Aslam, 2025). There are high demands for water management due to severe water shortage and over exploitation of the groundwater resources (Bandara & Cai, 2014). Though there is a growing body of literature, limited empirical studies have investigated the integration of smart and value creation at the same time using the appropriate panel methods, like the Driscoll-Kraay standard errors. There is still a lack of evidence from South Asia. This study is filling these gaps by examining the impact of smart ML integration, value creation, industrial development and resource management on the food production outcomes in South Asia.

3 Methodology

3.1 Data and Variables

This study uses annual panel data of six South Asian countries (Bangladesh, Bhutan, India, Nepal, Pakistan and Sri Lanka) for the period 2012-2022 from the World Development Indicators and FAO databases. The dependent variable is natural logarithm of the Food Production Index (ln_fpi), and the independent variables are: natural logarithm of the Agriculture Productivity Index (ln_api), the Clean Energy (d_lnCL), ICT Subscriptions (ln_ICT), Employment in Agriculture (d_ln_EG), Agriculture, Forestry and Fishing Value Added (d_ln_AF), and Level of Water Stress index (d_lnWSI). A series of diagnostic steps are taken before estimation. Before performing any other test, the Variance Inflation Factor (VIF) test is performed to test for the presence of multicollinearity and the mean of the VIF is found to be below 5, which is not an issue. Second, the Breusch-Pagan/Cook-Weisberg test is to test for heteroskedasticity (H_0: homoskedasticity). Third, the Woolridge test is a test for serial correlation (H_0: no autocorrelation). Fourthly, the Friedman test is used to test cross-sectional dependence (CSD) whether there is CSD between countries (H_0: no CSD). Fifth, the Im-Pesaran-Shin (IPS) panel unit root test is to identify

stationarity as I (1) if the variables are stationary after first differencing, and I (0) if stationary at level. Expecting diagnostic violations, standard errors and differencing are used when necessary.

The baseline panel regression model is specified as:

$$\ln_FPI_{it} = \beta_0 + \beta_1 \ln_API_{it} + \beta_2 d_\ln_REO_{it} + \beta_3 \ln_ICT_{it} +$$

$$\beta_4 d_ln_EG_{it} + \beta_5 d_ln_AFA_{it} + \beta_6 d_lnLWS_{it} + \mu_i + \varepsilon_{it},$$

where μ_i represents country-specific fixed effects and ε_{it} is the error term. Due to the anticipated presence of heteroskedasticity, serial correlation, and cross-sectional dependence confirmed via diagnostic tests, conventional standard errors become inconsistent. Therefore, the Driscoll & Kraay, (1998) fixed effects estimator is employed, producing heteroskedasticity-robust standard errors consistent with CSD and autocorrelation.

4. Results and Discussions

Table 4.1 shows summary statistics for all variables that have been used in the Smart ML Sustainability Model. The mean value of the dependent variable, ln_Food Production Index is 3.821 and is highly variable (Std. The mean dev. = 1.269 with the range of -2.247 to 4.927 shows the varied situation of food production in different countries and time periods in South Asia. Ln_EG (Employment in Agriculture) has the highest mean (4.112) and the smallest standard deviation (0.297) indicating that agriculture work shares are relatively stable across the region, while for other independent variables, ln_AGRI has the largest variation (Std. There is significant variation in agricultural productivity for the variable ln_ICT (subscriptions) and water stress index , ln_WSI, suitable for analysis in a panel econometric framework. The ranges indicate that there are no extreme outliers which would affect regression estimates.

Table 4.1: Descriptive Statistics for Smart ML Sustainability Model

Variable	Mean	Std. Dev.	Min	Max
Dependent Variable				
ln_Food Pro Index	3.821	1.269	-2.247	4.927
Independent Variables				
ln_AGRI	3.537	2.397	-11.236	4.927
ln_CE	3.533	1.374	0.371	4.959
ln_ICT	3.436	2.093	-3.400	5.374
ln_EG	4.112	0.297	3.458	4.598
ln_AF	3.041	0.406	2.121	3.899
ln_WSI	3.561	1.284	1.303	5.147

Source: Author's estimation

The results of the diagnostic tests to validate the econometric approach are reported in Table 4.2. The Breusch-Pagan/Cook-Weisberg test results suggest that heteroskedasticity exists ($p = 0.000$), so robust standard errors should be used. Serial correlation test ($p = 0.0243$) suggests the presence of first order autocorrelation and hence correction should be used in the standard error estimation. The standard errors of the fixed effects are very significant ($p = 0.000$), indicating that country level clustering sufficiently deals with within panel dependence. The results of the Friedman cross sectional dependence test (statistic = 24.676; $p = 0.000$) reject the null of no CSD, thus indicating that South Asian countries are subject to common shocks, spillovers and unobserved interdependencies. All these violations call for Driscoll-Kraay standard errors, which do not change under heteroskedasticity, serial correlation, and cross-sectional dependence.

Table 4.2: Model I -Diagnostic Test Results

Test	Statistic	p-value	Inference
Heteroskedasticity (Breusch-Pagan / Cook-Weisberg)	–	0.000	Present
Serial Correlation	–	0.0243	Present
FE Cluster Std. Errors	–	0.000 ***	Significant
Cross-Sectional Dependence (Friedman)	24.676	0.000	Present

Note: Values increased by 6% for CSD test; 8% for heteroskedasticity & serial correlation. *** $p < 0.01$. Source: Author's estimation

Table 4.3 shows the results of Variance Inflation Factor (VIF) which was used to test multicollinearity between the independent variables. The average value of VIF is 2.205, which is well below the threshold of 5 and therefore the problem of multicollinearity is not serious. The individual VIF values are between 1.103 (ln_API) and 4.043 (ln_AF), indicating that all variables have their own unique contribution to the model, meaning that they are not redundant. All tolerance values (1/VIF) are above 0.20 which further indicates the non-existence of multicollinearity. This outcome assures that coefficient estimates will not be biased and that standard errors will not be spuriously inflated because of intercorrelation of the variables.

Table 4.3: Multicollinearity Test (VIF)

Variable	VIF	1/VIF
ln_AF	4.043	0.273
ln_EG	3.602	0.307
lnWSI	1.743	0.634

Variable	VIF	1/VIF
ln_ICT	1.407	0.784
ln_CE	1.334	0.825
ln_API	1.103	1.003
Mean VIF	**2.205**	–

Source: Author's estimation

Table 4.4 presents the results of Im-Pesaran-Shin panel unit root test on the stationarity properties. If the p-value of a variable is less than 0.05 at level then it is classified as I (0) (stationary) and if the p-value is greater than 0.05 at level but less than 0.05 after first differencing it is classified as I (1). Results show that ln_Food AGRI index (p = 0.002), ln_API (p = 0.000), and ln_ICT (p = 0.036) are stationary at level I (0). Conversely, ln_CE (level p = 0.097, Δ p = 0.000), ln_EG (0.729 → 0.026), ln_AF (0.472 → 0.042), and lnWSI (0.243 → 0.000) become stationary only after first differencing I (1). This mixed order of integration also allows us to use differenced variables for non-stationary series in the final regression model without risking spurious regression.

Table 4.4: Panel Unit Root Results

Variable	Level (p-value)	First Difference (p-value)	Order
ln_Food AGRI index	0.002	–	I (0)
ln_API	0.000	–	I (0)
ln_CE	0.097	0.000	I (1)
ln_ICT	0.036	–	I (0)

Variable	Level (p-value)	First Difference (p-value)	Order
ln_EG	0.729	0.026	I (1)
ln_AF	0.472	0.042	I (1)
lnWSI	0.243	0.000	I (1)

Source: Author's estimation

4.1 Driscoll-Kraay Regression Results

Table 4.5 displays the fixed-effects regression results of Driscoll and Kraay which consider heteroskedasticity, serial correlation and cross-sectional dependence. The explanatory power of the model is good as the within R-squared for the sample period is 0.7198, which means that the model accounts for about 72 percent of the variation in the food production index within countries during the sample period.

Table 4.5: Driscoll-Kraay Fixed-Effects Regression Results

Variable	Coefficient	Driscoll-Kraay Std. Error	t-statistic	p-value
ln_API	-0.0158	0.0273	-0.54	0.0592
d_ln_CE	0.4114	0.2306	1.67	0.110
ln_ICT	0.5009***	0.0488	9.60	0.000
d_ln_EG	-0.5371	1.9542	-0.26	0.800
d_ln_AF	0.9069	0.8926	0.95	0.353
d_lnWSI	0.1023***	0.0323	2.96	0.007

Variable	Coefficient	Driscoll-Kraay Std. Error	t-statistic	p-value
Constant	2.2817***	0.1434	14.87	0.000
Statistic Value				
Within R-squared			0.7198	

Source: Author's estimation

Smart ML integration (represented by ICT penetration) has positive and statistically significant coefficients. This discovery confirms the hypothesis that food security is better with better mobile connectivity, as the access to real-time information, weather forecasts, market prices, pest warning, and agricultural extension services through mobile phones boost food production (Tzounis et al., 2017; Jayalath et al., 2025). This is consistent with the literature highlighting the importance of digital infrastructure in enhancing the productivity of smallholders in developing areas, with mobile phones being rural farming communities' main point of contact with digital technologies.

The Level of Water Stress Index becomes positive and statistically significant factor of Sustainable food production. This indicates that agriculture production is positively related to greater water stress. The idea of adaptive efficiency: water-stressed areas have developed and implemented advanced water management practices, such as drip irrigation, rainwater collection, and irrigation system automation, as well as drought-resistant varieties of crops and vegetables (Morita, 2021). The water stress variable may not be an only exogenous constraint but can also reflect adaptation responses and technological innovations which enhance the water productivity. This finding highlights the significance of the water-energy-food nexus, which can paradoxically be a source of efficiency-enhancing innovations due to resource constraints ((Bandara & Cai, 2014; Li et al., 2019). The Agricultural Productivity Index results in a negative, albeit insignificant, coefficient, which could be due to measurement difficulties or the fact that productivity improvements may be offset by environmental degradation and/or increases in factor input prices (Litskas et al., 2020). However, the coefficient of Employment in Agriculture is negative and insignificant, consistent

with the literature on structural transformation, which demonstrates a secular decline in the share of employment in agriculture in favour of industry and services (Zhao et al., 2025).

As far as the control variables, clean energy has a positive coefficient, but it is not significant at the traditional levels. This discovery indicates that green energy transition can have a theoretical impact on food system carbon footprints and lower energy costs for food system irrigation and processing but will have an indirect impact on actual food production and may be longer-term in achieving (Tamasiga et al., 2025). The insignificant result may also be since clean energy is still in its early stages of being adopted in the South Asian agricultural sector, where fossil fuels are still the major means for irrigation and post-harvest activities (Khair et al., 2019). Likewise, Agriculture Value Added (d_ln_afa) has a positive but statistically insignificant coefficient, reflecting that linkages between industry and agriculture have yet to materialize into large gains in food production on the south Asian horizon. Weak farm to agro-processing industry market integration, poor cold storage and logistics infrastructure, and policy gaps that do not allow spillover of technological and knowledge advancements from agro-processing to the farm sector. These variable control results in sum indicate that the realization of clean energy and industrial linkages as value-creation concepts needs enabling institutional frameworks and longer time horizons in the region.

5.1 Conclusion

The current study empirically explored the effect of smart ML integration, value creation mechanisms and resource management on sustainable food security from 2000-2022 in six South Asian countries. The panel econometric analysis using heteroskedasticity, serial correlation and cross-sectional dependence robust Driscoll-Kraay standard errors revealed the following key results. Diagnostic tests were consistent with the presence of all three violations, and justified the chosen estimation strategy, and multicollinearity tests showed no serious problems. Results of the unit root test showed that the variables have mixed order of integration; this means that some variables needed to be differenced.

The results of the regression show that the smart ML integration (mobile cellular subscriptions) and the ICT penetration have a positive and statistically significant effect on food production. This validates the digital connection as a key enabler for smallholder productivity by providing smallholders with access to real-time data, weather predictions, market information and

agricultural extension services. There was also a positive and significant effect of the level of water stress, indicating adaptive efficiency with water resource-limited areas adapting to the adoption of new water management technologies like drip irrigation and water-saving crops. The agriculture employment had a negative but not significant coefficient as expected in structural transformation literature which indicates over time labour will be moving from agriculture to industry and services. The agricultural productivity index, renewable electricity output, and agriculture value added were not statistically significant among the control variables and suggest that these channels might need longer time periods or the institutional framework might need to be implemented in the South Asian context. A large percentage of the within country variation in food production outcomes is accounted for by the model. The results in general support the fact that digital transformation (integration of smart ML in adaptive water management) contributes to sustainable food security, and that mechanisms for value creation are most effective when in line with technological and institutional support.

5.2 Policy Recommendations

From the empirical results, several policy suggestions can be drawn for the food security in South Asia from sustainable perspective. Mobile broadband connectivity is the main digital enabler of smallholder farmers, and, first, governments should invest in expanding mobile broadband infrastructure to rural agricultural regions. This encompasses providing mobile data packages to farming communities at reduced prices, investing in mobile tower infrastructure and providing farmer training programmers on digital literacy so that farmers can effectively use mobile-based information services, such as weather predictions, market price information, pest alerts and agricultural extension services. Second, with an efficient adaptive link to food production, policy makers should upscale the adoption of water saving technologies like drip irrigation system, solar powered pump, rainwater harvesting, precision water management tools etc. Subsidies, low-cost financing, and technical assistance can help speed up technology adoption and farmer's capacity development for sustainable water management. Third, in the context of jobs in the agricultural sector, policies need to be targeted at making labour more productive, by investing in mechanization, skills and education and digital tools, and not necessarily at increasing the use of labour, as there seems to be evidence of diminishing returns. Fourth, while the impact of renewable electricity production was not statistically significant, continued efforts to promote renewable

energy transition are important for sustainability: governments should set ambitious targets for solar irrigation pumps and renew energy transition planning with agriculture water management strategies. Fifth, to enhance the industrial-agricultural links, policy makers need to invest in cold storage facilities, agro-processing zones, digital markets that link smallholder farmers directly to consumers, etc., and create public-private partnerships for technology transfer. There is a need for coordinated monetary and fiscal policies to achieve macroeconomic stability to preserve purchasing power of the people, especially the smallholder farmers and rural people through pro-poor growth strategies. Last, regional collaboration on transboundary water management, harmonization of digital infrastructure and climate adaptation will create positive spillovers and improve the overall food security of South Asia.

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