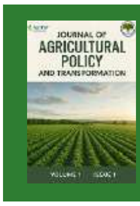

Journal of Agricultural Policy and Transformation *(AgriPaT)*
ISSN: 3134-819X
Journal Homepage: http://www.ageconfrontiers.com/agripat
Vol. 2(3) Open Access

Carbon and Water Footprints of Cotton Production in Punjab, Pakistan: Implications for Climate-Smart Agricultural Policy

Muhammad Umar Farooq1,*, Amnan Javaid2, Abdul Mateen3 & Hafiz Muhammad Irfan2
[1] Institute of Agricultural and Resource Economics, University of Agriculture, Faisalabad, Pakistan
[2] Department of Economics, GC University, Faisalabad, Pakistan
[3] Airlangga University, Surabaya, Indonesia
** Corresponding author:* economist866@gmail.com

ARTICLE INFO

Keywords
- *Cotton*
- *Carbon Footprint*
- *Water Footprint*
- *Climate Smart Agriculture*
- Water Use Efficiency
- *Agricultural Policy*

Article History
Received: 18 June 2026
Revised: 25 June 2026
Accepted: 26 June 2026
Available online: 26 June 2026

DOI
10.66529/agripat.2026.2.3.96

ABSTRACT

Cotton is a cornerstone of Pakistan's agricultural economy and textile industry, yet its production contributes substantially to greenhouse gas emissions and water consumption. This study assessed the carbon footprint (CF), water footprint (WF), and water-use efficiency (WUE) of cotton production among 200 farm households in District Vehari, Punjab, categorized as small, medium, and large farms. Results showed an average carbon footprint of 613.2 kg CO_2-eq per acre, with electricity, diesel, and urea accounting for nearly 89% of total emissions. Significant differences in CF and WUE were observed across farm sizes, while the average water footprint of seed cotton (7.23 m^3/kg) did not vary significantly. Regression analysis revealed that farm size and education positively influenced CF, whereas household income had a negative effect. The findings highlight the need for targeted interventions in irrigation management, energy use, input efficiency, and extension services. The study provides farm-size-specific evidence to support climate-smart cotton production and sustainable resource management in Pakistan.

Citation: *Farooq, M.U., Javaid, A., Mateen, A. & Irfan H.M. (2026). Carbon and water footprints of cotton production in Punjab, Pakistan: Implications for climate-smart agricultural policy.* J. Agric. Pol. & Transf. 2(3):127-139.
https://doi.org/10.66529/agripat.2026.2.3.96

1. INTRODUCTION

Agriculture remains the structural backbone of Pakistan's economy, contributing approximately 19% of national gross domestic product (GDP) and absorbing a substantial share of the rural labor force, either directly or through agriculture-linked industry (Government of Pakistan, 2024). Within this sector, cotton occupies a uniquely central position: Pakistan is the world's fourth-largest cotton producer after India, China, and the United States, and the crop forms the raw material base for a textile industry that, as of the mid-2020s, still accounts for the majority of Pakistan's merchandise export earnings (USDA, 2025). Cotton cultivation is concentrated in Punjab, which contributes roughly four-fifths of national cotton area and output, with the remainder produced in Sindh. Within Punjab, the southern belt encompassing Multan, Muzaffargarh, Vehari, Bahawalpur, and Bahawalnagar districts forms the crop's traditional heartland (GoP, 2024).

Two interconnected resource pressures increasingly define the sustainability of this production system. The first is climate change, to which Pakistan is repeatedly ranked among the most vulnerable countries globally despite contributing a negligible share of cumulative global emissions (Germanwatch, 2025). Rising mean temperatures, more frequent heatwaves, and increasingly erratic monsoon rainfall have measurably reduced cotton yields in Punjab and Sindh; the 2022 floods caused over USD 30 billion in economic losses and damaged a large share of standing cotton crop, and further disruptions in 2024-25 contributed to a reported 13.5% contraction in major crop output in fiscal year 2024-25 (World Bank, 2023; Ministry of National Food Security and Research, 2025). The second pressure is water scarcity: Pakistan's per-capita water availability has fallen toward levels conventionally classified as scarce, driven by glacial melt variability, inefficient on-farm water application, and rapid groundwater depletion in canal-command areas (Watto & Mugera, 2015). Agriculture absorbs roughly 90% of Pakistan's freshwater withdrawals, and cotton as an irrigation-intensive crop grown in hot, semi-arid plains sits at the center of this tension between productivity and resource sustainability.

Carbon footprint (CF) and water footprint (WF) accounting have emerged as the principal quantitative tools for benchmarking agricultural systems against these twin pressures (Wiedmann & Minx, 2008; Hoekstra et al., 2011). Both metrics have become standard instruments in agri-food sustainability research and, increasingly, in the design of climate-smart agriculture (CSA) programs, government subsidy schemes, and voluntary carbon-market mechanisms aimed at the agricultural sector (Imran et al., 2022; Khan & Ali, 2024).

Despite cotton's centrality to Pakistan's economy and its water and emissions profile, farm-level evidence on CF and WF disaggregated by farm size remains comparatively sparse for the Vehari cotton belt. The existing literature on Pakistani cotton footprints is geographically concentrated in Muzaffargarh (Imran et al., 2018) and in supply-chain-level analyses (Khan & Ali, 2024); farm-size-specific, joint carbon and water footprint assessments for Vehari have not, to the authors' knowledge, been previously published. This gap matters for policy: differentiated farm-size categories face different input-use patterns, different access to credit and extension, and different capacities to adopt CSA technologies, so footprint findings that are not disaggregated by farm size risk producing one-size-fits-all recommendations that fit no actual category of farmer well. Moreover, Vehari's position within the Lower Bari Doab Canal (LBDC) command area, one of the most intensively irrigated zones in Punjab, makes it a particularly salient case for water governance research (Makhdum et al., 2018).

The specific novelty of this paper lies in three elements: (i) it provides the first comprehensive, jointly estimated CF and WF dataset for cotton in Vehari district; (ii) it disaggregates both footprints and WUE by farm-size category, enabling genuinely differentiated policy targeting; and (iii) it applies a full suite of regression diagnostic tests including VIF, Breusch-Pagan, and Shapiro-Wilk procedures to the CF determinants model, improving upon the methodological completeness of earlier Pakistani CF studies. The research objectives are to: (i) estimate the CF of cotton production, disaggregated by input source and farm-size category; (ii) estimate WUE and WF of cotton production with appropriate statistical characterization; (iii) identify the socio-economic and farm-management determinants of CF using multiple linear regression with full diagnostics; and (iv) derive a differentiated, farm-size-specific policy package of instruments aligned with Pakistan's CSA and water-governance reform agenda. The paper is structured as follows: Section 2 reviews the relevant literature; Section 3 describes the study area, sampling, and estimation methods; Section 4 presents results; Section 5 discusses findings; Section 6 concludes with policy recommendations.

2. Literature Review

Climate Change, Agriculture, and Greenhouse Gas Accounting

The scientific consensus that anthropogenic GHG emissions drive global temperature increases, with attendant risks to agricultural productivity, has been long established (IPCC, 2007) and has only sharpened in subsequent assessment cycles (IPCC, 2021). Agriculture contributes an estimated one-tenth to one-eighth of total anthropogenic GHG emissions worldwide, arising principally from fertilizer manufacture and application, fuel combustion in farm machinery and irrigation pumping, enteric fermentation in livestock, and land-use change (Browne et al., 2011). Because emissions associated with specific crops and farming systems vary considerably with input intensity, irrigation technology, and regional energy mix, CF accounting at the farm or crop level has become the standard tool for identifying where mitigation effort can be most efficiently targeted (Pandey et al., 2011).

South Asian evidence on agricultural carbon footprints has expanded substantially over the past decade. Early work by Pathak and Wassmann (2007) generated technical coefficients for rice-based systems in India. Subsequent studies extended carbon accounting to wheat, potato, and other staple crops across the region. For cotton specifically, Imran et al. (2018) estimated energy efficiency and GHG emissions for cotton growers in southern Punjab and found fertilizer, diesel, and electricity to be the dominant emission sources, a pattern consistent with broader South Asian cotton studies from Iran (Komleh et al., 2012) and Australia (Maraseni et al., 2010). A more recent study by Kaur et al. (2025), comparing paddy-wheat and cotton-wheat rotations across two districts of Indian Punjab, found that cotton-wheat systems generated substantially lower per-hectare emissions than paddy-wheat systems, and that resource-conservation technologies such as direct-seeded rice and crop-residue management could cut emissions from individual operations by more than half. This evidence underscores both the comparatively favorable emissions profile of cotton relative to paddy systems and the scope for targeted technological mitigation within cotton-based rotations.

A critical unresolved question in this literature concerns the extent to which CF variation across farms reflects structural farm-size effects versus management-driven differences in input intensity. Studies to date have rarely disentangled these mechanisms at the farm level within a single district. The present study addresses this gap by

| https://doi.org/10.66529/agripat.2026.2.3.96

disaggregating both CF and WUE by farm-size category within a single well-defined agro-climatic setting, enabling more precise attribution of emissions to structural versus behavioral determinants.

Water Scarcity, Water Footprints, and Cotton

The WF concept, formalized by Hoekstra and Hung (2002) and elaborated by Chapagain and Hoekstra (2004) and Hoekstra et al. (2011), decomposes water consumption embedded in a product into green water (effective rainfall), blue water (surface and groundwater abstraction), and grey water (water required to assimilate pollution). Cotton has attracted particular attention within this literature because, although it occupies a small share of global arable land, it is highly water-intensive: Chapagain et al. (2006) estimated that global cotton consumption embeds roughly 256 km^3 of water annually and identified Pakistan, alongside India, Uzbekistan, and Egypt, among the most water-intensive cotton-producing countries. Subsequent work has confirmed that cultivation and ginning, rather than downstream textile manufacture, account for the largest share of cotton's WF in producer countries such as Pakistan (Khan & Ali, 2024).

Pakistan's water situation has deteriorated further since earlier cotton-footprint studies were conducted. National-level evidence indicates that Pakistan's average cotton water productivity is approximately 0.28 kg/m^3, well below comparable benchmarks in other producing countries, and that WUE in Pakistani cotton systems could realistically be raised by 46–54% through improved irrigation scheduling and management alone (Jamil et al., 2021). Against this backdrop, WUE defined in this study as the ratio of crop water requirement to total water applied (see Section 3 for methodological justification) has become a policy-relevant indicator, distinct from WF per unit of output, because it captures the scope for on-farm water savings without necessarily altering yield. Watto and Mugera (2015) further demonstrate that groundwater irrigation efficiency in Punjab varies systematically with access to private tube wells, a factor that intersects closely with farm size in Pakistani agrarian structure.

The relationship between farm size and water efficiency is theoretically ambiguous and empirically contested: while some studies find that smaller farms achieve higher allocative efficiency due to tighter resource constraints and more labor-intensive management (Ali & Byerlee, 1991), others find that larger farms benefit from economies of scale in irrigation infrastructure (Watto & Mugera, 2015). This study contributes an empirical test of this relationship within the specific agro-ecological and institutional context of the LBDC command area.

Climate-Smart Agriculture and Cotton-Sector Policy in Pakistan

The Food and Agriculture Organization's (FAO) climate-smart agriculture (CSA) framework, seeking simultaneously to raise productivity, build resilience, and reduce emissions, has become the dominant policy lens through which donor and government programs in Pakistan approach crop-sector reform (Imran et al., 2022). Empirical work applying this framework to Punjab's cotton belt has found that adopters of CSA practices, including improved irrigation scheduling, integrated pest management (IPM), and water-saving technologies, achieve materially better financial and resource-use outcomes than conventional growers in LBDC-command areas (Makhdum et al., 2018; Imran et al., 2018). The World Bank's Punjab Resilient and Inclusive Agriculture Transformation (PRIAT) Project, a USD 200 million credit program, explicitly targets improvements in agricultural water productivity and reduction of head-to-tail inequities in canal water distribution, both of which bear directly on the WUE disparities this study documents across farm-size categories (World Bank, 2024).

Pakistan's broader policy architecture also provides important context. The National Climate Change Policy (2021), the National Water Policy (2018), and the Agriculture Transformation Plan (2022) collectively establish ambitions for GHG mitigation, water-use efficiency improvement, and productivity enhancement in the crop sector. However, the translation of these national-level ambitions into farm-size-differentiated implementation instruments has remained incomplete, a gap that the policy recommendations in Section 6 of this paper are specifically designed to address.

On the production side, Pakistan's cotton sector experienced a pronounced decline in area and output through the early-to-mid 2020s, driven by pest pressure (particularly pink bollworm), heat stress during flowering, and farmer disillusionment with returns relative to competing crops. Cotton area reportedly fell by more than two-fifths over the preceding decade (USDA, 2025). In response, the federal government constituted a Cotton Production Enhancement Committee in 2025 and launched an early-planting campaign with per-hectare subsidies for the 2025-26 season, alongside renewed attention to seed quality and IPM (USDA, 2025). These policy responses confirm that CF and WF findings from farm-level studies retain direct relevance to an active area of national agricultural policy deliberation.

Taken together, this literature establishes three things relevant to the present study. First, cotton's CF and WF in Pakistan are dominated by a small number of input categories, principally electricity, diesel, and nitrogenous fertilizer, and by irrigation practice rather than crop water demand as such. Second, both footprint outcomes vary systematically with farm management rather than technical parameters being fixed, implying genuine scope for policy-induced improvement. Third, existing Pakistani CF studies have not provided Vehari-specific, farm-size-disaggregated evidence with rigorous statistical diagnostics, the gap this study fills.

3. Materials and Methods

Study Area

The study was conducted in District Vehari, located in the cotton-growing belt of southern Punjab, Pakistan (approximately 29°-30°N, 71°-72°E). Vehari comprises three tehsils, Vehari, Burewala, and Mailsi, all included in the sampling frame. The district lies within the Lower Bari Doab Canal (LBDC) command area and is characterized by a semi-arid climate with mean summer temperatures of 35-40°C, predominantly clay-loam soils with moderate fertility, and an agriculture dominated by cotton-wheat rotation. Vehari was selected purposively because it is among the established cotton-producing districts of southern Punjab and, critically, because farm-level CF and WF evidence specific to the district, disaggregated by farm size, had not been comprehensively documented prior to this study. Informed verbal consent was obtained from all participants prior to interview, consistent with standard practice for non-sensitive agricultural household surveys. No personally identifiable information was retained in the analysis dataset.

Sampling Procedure and Sample Size

A two-stage stratified random sampling procedure was employed. In the first stage, the three tehsils of Vehari were treated as sampling clusters. In the second stage, a total of 200 cotton-growing farm households were randomly selected across these clusters using village-level farmer lists obtained from local agricultural extension offices as the sampling frame. The sample size was determined using the Cochran (1977) formula for proportions [$n = Z^2pq/e^2$], with a 95% confidence level ($Z = 1.96$), an assumed population proportion of $p = 0.5$ (maximum variance), and a margin of error of $e = 0.07$, yielding a minimum required sample of 196, rounded to 200 to provide a margin against non-response and to allow equal sub-group representation. Primary data were collected between November 2023 and February 2024 through face-to-face interviews using a structured questionnaire of 59 items, covering household demographics, landholding and tenancy status, input use (seed, fertilizer, pesticide, irrigation source and frequency, machinery and fuel use, electricity use, and labor), and farmer-reported management practices. Sampled households were classified into three farm-size categories following the Pakistani agricultural-census convention: small farms (<5 acres, $n = 81$); medium farms (5–12.5 acres, $n = 64$); and large farms (>12.5 acres, $n = 55$).

Carbon Footprint Estimation

The CF of cotton production was estimated using the standard emission-coefficient approach widely applied in farm-level GHG accounting (Lal, 2004; Dyer & Desjardins, 2003). Under this approach, the physical quantity of each input applied per acre is multiplied by an input-specific GHG emission coefficient (kg CO_2-eq per unit), and the resulting emissions are summed across all input categories to yield total CF per acre:

$$CF = \Sigma (Qi \times EFi)$$

where Qi is the quantity of input i applied per acre and EFi is the emission factor for input i. The emission coefficients applied are presented in Table 1, with the rationale for each coefficient as follows. The diesel emission factor (2.76 kg CO_2-eq/L) follows Dyer and Desjardins (2003), who derived combustion-based factors for agricultural diesel encompassing both direct CO_2 and upstream fuel-cycle emissions; this coefficient is consistent with values used in comparable Pakistani cotton studies (Imran et al., 2018). The electricity emission factor (0.489 kg CO_2-eq/kWh) follows Garcia (2011), whose life-cycle approach for developing-country electricity generation is appropriate given Pakistan's thermal-heavy national grid. Fertilizer emission factors follow Lal (2004), who provides a comprehensive synthesis of nitrogen (1.30 kg CO_2-eq/kg N), phosphorus (0.20 kg CO_2-eq/kg P_2O_5), and potassium (0.20 kg CO_2-eq/kg K_2O) coefficients encompassing both manufacturing and field-application emissions. Pesticide emission factors follow the same source (Herbicide: 6.30; Insecticide: 5.10 kg CO_2-eq/kg active ingredient). Use of published generalized coefficients, rather than locally measured factors, is an acknowledged limitation (see Section 5); it is, however, the standard approach in farm-level CF studies where site-specific emission measurements are not feasible. Farmyard manure was excluded from the CF calculation because no consensus net GHG emission coefficient exists for this input in the consulted literature, consistent with the convention in comparable Pakistani and South Asian farm-level studies (Imran et al., 2018). This exclusion may result in minor underestimation of total CF for farms applying substantial farmyard manure quantities; the directional bias is, however, likely to be consistent across farm-size categories.

Table 1. Greenhouse gas emission coefficients applied to farm input use.

Input	Unit	GHG Emission Coefficient (kg CO_2-eq per unit)	Source
Diesel fuel	Litre	2.76	Dyer and Desjardins (2003)
Electricity	kWh	0.489	Garcia (2011)
Nitrogen (N)	kg	1.30	Lal (2004)
Phosphorus (P_2O_5)	kg	0.20	Lal (2004)
Potassium (K_2O)	kg	0.20	Lal (2004)
Herbicide (active ingredient)	kg	6.30	Lal (2004)
Insecticide (active ingredient)	kg	5.10	Lal (2004)

Note: All coefficients represent kg CO_2-equivalent per unit of input. Farmyard manure is excluded because no validated net GHG emission coefficient is available in the consulted literature.

Water Footprint and Water-Use Efficiency

The WF of cotton production was decomposed, following Hoekstra et al. (2011) and Chapagain and Hoekstra (2004), into green water use (effective rainfall consumed by the crop) and blue water use (irrigation water abstracted from canal or groundwater sources). Crop water requirement (CWR) and effective rainfall were estimated using the FAO CROPWAT 8.0 model (FAO, 2010), with reference evapotranspiration (ETo) calculated using the Penman-Monteith method with monthly climatic data (temperature, humidity, wind speed, sunshine hours) sourced from the Pakistan Meteorological Department station at Multan (the nearest full-data station to Vehari). Crop coefficients (Kc: initial = 0.35, mid-season = 1.20, late-season = 0.60) followed FAO Irrigation and Drainage Paper No. 56 (Allen et al., 1998) for upland cotton, calibrated to the district's planting calendar (May–June sowing; October–November harvest). Effective rainfall was estimated using the USDA soil conservation service method within CROPWAT. Total CWR was thereby estimated at 1,100 mm per season. The WF per unit of output (m^3/kg of seed cotton) was computed as:

$$\text{WF} = (\text{Green water} + \text{Blue water}) / \text{Yield}$$

WUE was computed as the ratio of CWR to total water applied by the farmer (WUE = CWR / Total water applied). This definition differs from the more common agronomic formulation (Yield / Water consumed) and requires justification. The agronomic WUE metric is sensitive to yield variability arising from non-water factors (e.g., pest pressure, variety, and soil fertility), which are not the primary focus of this study and which could confound a purely irrigation-management signal. By using CWR / Total water applied, this study explicitly captures the degree of alignment between irrigation supply and biophysical crop demand, a metric more directly policy-actionable for irrigation scheduling and water-governance purposes. This approach is consistent with the irrigation efficiency framework applied by Watto and Mugera (2015) in their analysis of Punjab tube-well irrigation and has been employed in comparable CSA studies in South Asia (Jamil et al., 2021). A WUE approaching unity indicates that water applied closely matches crop requirement; values below unity indicate over-application or conveyance inefficiency. Both WUE and the conventional agronomic WF metric are reported in Section 4 to facilitate comparison with the broader literature.

Statistical Analysis: Determinants of Carbon Footprint

To identify the socio-economic and farm-management determinants of CF, a multiple linear regression (MLR) model was estimated using ordinary least squares (OLS):

$$CF_i = \beta0 + \beta1(\text{Education}_i) + \beta2(\text{Income}_i) + \beta3(\text{Farm size}_i) + \varepsilon_i$$

where CF_i is the carbon footprint (kg CO_2-eq/acre) of farm household i; Education_i is years of formal schooling of the household head; Income_i is total annual household income (PKR); Farm size_i is total cultivated area (acres); β0 is the intercept; β1–β3 are the coefficients to be estimated; and ε_i is the error term. The inclusion of only three explanatory variables is acknowledged as a limitation (see Section 5); however, it reflects the boundaries of the survey instrument rather than an analytical choice, and the variables included are those with the strongest theoretical and empirical prior for association with CF in the literature (Imran et al., 2018; Pandey et al., 2011).

Prior to estimation, the following diagnostic procedures were applied: (i) Pearson correlation matrix to identify potential collinearity among regressors; (ii) Variance Inflation Factor (VIF) and tolerance statistics to assess multicollinearity; (iii) Breusch-Pagan test for heteroscedasticity; (iv) Shapiro-Wilk test for normality of residuals;

and (v) scatter plots of standardized residuals against fitted values. Differences in CF, WF, and WUE across farm-size categories were evaluated using one-way analysis of variance (ANOVA) with Tukey's Honest Significant Difference (HSD) post-hoc tests. Statistical significance was assessed at the 5% level throughout. Analyses were conducted in IBM SPSS Statistics 27.

4. Results

Carbon Footprint

Table 2 presents the CF of cotton production per acre, disaggregated by input source and farm-size category, with descriptive statistics. Total CF averaged 554.6 ± 62.3 kg CO_2-eq/acre for small farmers, 654.0 ± 71.8 kg CO_2-eq/acre for medium farmers, and 631.1 ± 68.4 kg CO_2-eq/acre for large farmers, yielding a full-sample mean of 613.2 kg CO_2-eq/acre. One-way ANOVA confirmed that per-acre CF differences among farm-size categories were statistically significant [$F(2, 197) = 3.42$, $p = 0.034$; $\eta^2 = 0.033$], with Tukey HSD post-hoc tests indicating that small farmers differed significantly from both medium and large farmers ($p = 0.029$ and $p = 0.041$, respectively), while medium and large farmers did not differ significantly from each other ($p = 0.612$). When expressed per kilogram of seed cotton, CF averaged 0.678 kg CO_2-eq/kg for small farmers, 0.738 kg CO_2-eq/kg for medium farmers, and 0.656 kg CO_2-eq/kg for large farmers; ANOVA indicated these per-kilogram differences were not statistically significant [$F(2, 197) = 1.87$, $p = 0.157$].

Electricity was the single largest emission source across all categories, contributing 51%, 40%, and 48% of total CF for small, medium, and large farmers respectively. Diesel fuel contributed 26%, 36%, and 26% across the three categories; urea, the most significant fertilizer source, contributed 12%, 12%, and 14%. Together, electricity, diesel, and urea accounted for 88–89% of total CF in every farm-size category. The particularly high share of electricity emissions for small farmers (51%) relative to medium farmers (40%) reflects the greater reliance of small farmers on electric tube wells for groundwater pumping, while medium farmers' higher diesel contribution (36%) reflects greater use of hired diesel-powered machinery. Phosphatic and potassic fertilizers, weedicide, and other inputs contributed comparatively minor shares.

Table 2. Carbon footprint of cotton production by input source and farm-size category

Input	Small (kg CO_2-eq/acre)	%	Medium (kg CO_2-eq/acre)	%	Large (kg CO_2-eq/acre)	%
Urea	64.05	12	78.05	12	90.77	14
DAP	19.52	4	20.54	3	20.57	3
Nitrophosphate	2.77	<1	3.58	1	4.52	1
Potash	0.06	<1	0.32	<1	1.19	<1
NPK (Guara)	7.94	1	14.18	2	1.00	<1
Fertilizer subtotal	**94.34**	**17**	**116.67**	**18**	**118.05**	**19**
Electricity	282.65	51	264.29	40	302.52	48
Diesel fuel	144.28	26	235.75	36	166.41	26
Weedicide	6.53	1	7.04	1	7.20	1
Insecticide	26.76	5	30.27	5	36.91	6
Total	**554.56**	**100**	**654.03**	**100**	**631.09**	**100**

Note: Percentages are rounded and may not sum to exactly 100. Farmyard manure excluded (see Section 3). Full-sample mean CF = 613.2 ± 68.6 kg CO_2-eq/acre.

Table 3 benchmarks the Vehari CF estimates against comparable studies. The estimates lie below those reported for cotton in Muzaffargarh, Pakistan (780 kg CO_2-eq/acre; Imran et al., 2018) and in Narrabri, Australia (777 kg CO_2-eq/acre; Visser et al., 2014), but above estimates for cotton in Warangal, India (417 kg CO_2-eq/acre; Hillier et al., 2013) and for potato in Esfahan, Iran (401 kg CO_2-eq/acre; Komleh et al., 2012). Readers should note that all values are converted to a per-acre basis for comparability; where original studies reported per-hectare figures, values were divided by 2.471 to yield per-acre equivalents. The Kaur et al. (2025) entry is reported qualitatively because that study presents cotton-wheat emissions at the rotation level rather than as a cotton-only per-acre estimate.

Table 3. Comparison of Vehari carbon footprint estimates with published studies

Reference	Study Area	Crop	n	Carbon Footprint (kg CO_2-eq/acre)
This study (2026)	**Vehari, Punjab, Pakistan**	**Seed cotton**	**200**	**613.2 (overall average)**
Imran et al. (2018)	Muzaffargarh, Punjab, Pakistan	Cotton	150	780
Visser et al. (2014)	Narrabri, NSW, Australia	Cotton	n/a	777
Maraseni et al. (2010)	Queensland, Australia	Cotton	Secondary data	574
Kaur et al. (2025)†	Punjab, India	Cotton-wheat rotation	2 districts	Lower than paddy-wheat (relative)
Pathak & Wassmann (2007)	Haryana, India	Wheat	16 districts	538
Komleh et al. (2012)	Alborz, Iran	Cotton	57	483
Hillier et al. (2013)	Warangal, India	Cotton	48	417
Komleh et al. (2012)	Esfahan, Iran	Potato	300	401

Note: (†) Kaur et al. (2025) is reported qualitatively; the original study does not report a cotton-only per-acre CF strictly comparable to other entries. Per-acre values derived from per-hectare figures by dividing by 2.471.

Water-Use Efficiency and Water Footprint

Table 4 presents WUE by farm-size category. WUE was 0.805 ± 0.08 for small farmers, 0.778 ± 0.09 for medium farmers, and 0.688 ± 0.11 for large farmers. One-way ANOVA confirmed that these differences were highly statistically significant [$F(2, 197) = 8.91, p < 0.001; \eta^2 = 0.083$], with Tukey HSD post-hoc tests indicating significant differences between all pairwise category combinations (all $p < 0.05$). This pattern indicates that small farmers applied irrigation water considerably closer to the crop's biophysical requirement, while large farmers over-irrigated relative to crop requirement by a wider margin. Because the underlying CWR (1,100 mm) is held constant across farm sizes, these differences reflect irrigation practice and water-source management rather than crop water demand per se. This finding is consistent with the literature's general observation that larger landholdings, often having more secure or higher-volume access to groundwater via private tube wells, tend toward less precise water application than smallholders facing tighter water constraints (Watto & Mugera, 2015).

Table 4. Water-use efficiency and irrigation intensity by farm-size category

Farm Category	n (%)	WUE (Mean ± SD)	Crop Water Requirement (mm)	Mean Total Water Applied (mm)
Small farmers	81 (40.5%)	0.805 ± 0.08	1,100	1,366
Medium farmers	64 (32.0%)	0.778 ± 0.09	1,100	1,414
Large farmers	55 (27.5%)	0.688 ± 0.11	1,100	1,598
Full sample	**200 (100%)**	**0.757 ± 0.10**	**1,100**	**1,453**

Note: WUE = CWR / Total water applied. CWR is held constant at 1,100 mm across categories (FAO CROPWAT estimate). ANOVA: $F(2, 197) = 8.91, p < 0.001$.

Table 5 reports the WF of seed cotton and water productivity by farm-size category. The mean WF was 7.22 ± 0.42 m^3/kg for small farmers, 7.25 ± 0.38 m^3/kg for medium farmers, and 7.22 ± 0.45 m^3/kg for large farmers, with a full-sample mean of 7.23 ± 0.42 m^3/kg. One-way ANOVA indicated that WF differences across farm-size categories were not statistically significant [$F(2, 197) = 0.14, p = 0.871$]. This absence of a significant farm-size gradient in the per-kilogram WF is consistent with the fact that large farmers, despite lower WUE, also achieved higher yields, such that the two effects roughly offset in the per-kilogram calculation. This combination, i.e. lower WUE alongside a similar per-unit WF reveals that the water-saving opportunity for larger farms lies specifically in reducing absolute over-application rather than in the WF metric alone: a farm can simultaneously appear water-efficient on a per-kilogram-output basis while still over-irrigating relative to true crop requirement.

| https://doi.org/10.66529/agripat.2026.2.3.96

Table 5. Water footprint and water productivity of seed cotton by farm-size category

Farm Category	n (%)	Water Footprint (m^3/kg; Mean ± SD)	Water Productivity (kg/m^3; Mean ± SD)	Mean Yield (kg/acre)
Small farmers	81 (40.5%)	7.22 ± 0.42	0.82 ± 0.05 kg/m^3	1,040
Medium farmers	64 (32.0%)	7.25 ± 0.38	0.80 ± 0.06 kg/m^3	1,060
Large farmers	55 (27.5%)	7.22 ± 0.45	0.87 ± 0.07 kg/m^3	1,105
Full sample	**200 (100%)**	**7.23 ± 0.42**	**0.83 ± 0.06 kg/m^3**	**1,068**

Note: WF = (Green water + Blue water) / Yield. ANOVA for WF: F(2, 197) = 0.14, p = 0.871 (not significant). Water productivity = Yield / Total water applied (m^3).

These farm-level WF estimates are substantially smaller than the supply-chain-wide WF reported for Pakistan's cotton sector (22.6 m^3/kg of finished cotton fabric; Khan & Ali, 2024), underscoring that cultivation-stage WF represents only one segment of the much larger water footprint embedded in finished cotton textile products. Table 6 places these results alongside national and international benchmarks.

Table 6. Comparison of water footprint and water-use efficiency results with national and international benchmarks.

Reference	Study Area	Indicator	Value	Crop / Scope
This study (2026)	**Vehari, Pakistan**	**Water footprint (green + blue)**	**7.23 m^3/kg ± 0.42**	**Seed cotton, farm-level**
This study (2026)	**Vehari, Pakistan**	**WUE (CWR/water applied)**	**0.69–0.81 (range across categories)**	**Seed cotton, farm-level**
Jamil et al. (2021)	Pakistan (national)	Water productivity	0.28 kg/m^3 (~3.57 m^3/kg)	Seed cotton; blue water focus
Jamil et al. (2021)	Pakistan (national)	WUE improvement potential	46–54%	Estimated achievable gain
Khan & Ali (2024)	Pakistan (supply chain)	Water footprint	22.6 m^3/kg	Finished cotton fabric, full chain
Chapagain et al. (2006)	Punjab, Pakistan	Blue water footprint	1.90 m^3/kg	Seed cotton, 1997–2001 period
Watto & Mugera (2015)	Punjab, Pakistan	Groundwater irrigation efficiency	Lower for water buyers	Cotton, tube-well comparison

Note: Indicators are not methodologically identical (water productivity, WF, and WUE are related but distinct metrics; see Section 3) and are presented for contextual benchmarking rather than direct numerical equivalence. The Khan & Ali (2024) figure spans the full textile supply chain and is substantially larger than farm-level cultivation-stage figures. Carbon footprint benchmarks are presented separately in Table 3 to avoid conflating footprint types.

Determinants of Carbon Footprint

Table 7 presents the MLR results. The model was statistically significant overall [F(3, 196) = 4.44, $p < 0.001$], explaining 14.8% of the variance in CF (adjusted $R^2 = 0.112$). The estimated equation with unstandardized coefficients is:

$$CF = 257.38 + 7.46 \times \text{Education} - 0.003 \times \text{Income} + 81.69 \times \text{Farm size} + \varepsilon$$

Farm size was the strongest and most statistically significant predictor ($\beta = 0.315$, $p < 0.001$; 95% CI [37.73, 125.64]), confirming the descriptive pattern in Section 4 that larger landholdings are associated with higher absolute CF. Education was positively and significantly associated with CF ($\beta = 0.160$, $p = 0.019$; 95% CI [1.23, 13.70]). Total household income was negatively and significantly associated with CF ($\beta = -0.206$, $p = 0.003$; 95% CI [−0.005, −0.001]).

| https://doi.org/10.66529/agripat.2026.2.3.96

Table 7. Multiple linear regression results: determinants of carbon footprint

Variable	β	SE	β (Standardized)	t	p	95% CI
(Constant)	257.38	85.94	—	2.995	0.003	[86.74, 428.03]
Education (years of schooling)	7.46	3.16	0.160	2.360	0.019	[1.23, 13.70]
Total household income (PKR)	−0.003	0.001	−0.206	−2.988	0.003	[−0.005, −0.001]
Farm size (acres)	81.69	22.29	0.315	3.665	<0.001	[37.73, 125.64]

Note: $R^2 = 0.148$; Adjusted $R^2 = 0.112$; $F(3, 196) = 4.44$, $p < 0.001$. 95% CI = 95% confidence interval for unstandardized coefficient β.

Table 8 presents diagnostic test results. VIF values ranged from 1.08 to 1.24, and tolerance values ranged from 0.81 to 0.93, indicating no problematic multicollinearity (all VIF < 10; all tolerance > 0.10). The Pearson correlation between farm size and household income was $r = 0.22$ ($p = 0.002$), representing a modest positive correlation that did not rise to the level of collinearity concern. The Breusch-Pagan test did not reject the null hypothesis of homoscedasticity [$\chi^2(3) = 5.12$, $p = 0.163$], and the Shapiro-Wilk test indicated approximately normally distributed residuals ($W = 0.987$, $p = 0.074$). Visual inspection of residual-versus-fitted plots corroborated these findings. Collectively, the OLS assumptions of no multicollinearity, homoscedasticity, and normality of residuals are supported by the diagnostics, lending confidence to the inference drawn from the coefficient estimates.

Table 8. Regression diagnostic test results.

Diagnostic Test	Test Statistic / Result	Interpretation
Multicollinearity (VIF)	Education: 1.08; Income: 1.24; Farm size: 1.19	All VIF < 10; tolerance > 0.80; no evidence of multicollinearity
Heteroscedasticity (Breusch-Pagan test)	BP $\chi^2(3) = 5.12$, $p = 0.163$	Null hypothesis of homoscedasticity not rejected at 5% level
Normality of residuals (Shapiro-Wilk)	$W = 0.987$, $p = 0.074$	Residuals are approximately normally distributed
Model specification (F-test)	$F(3, 196) = 4.44$, $p < 0.001$	Model jointly significant
Pearson correlation (farm size vs. income)	$r = 0.22$, $p = 0.002$	Moderate positive correlation; VIF confirms manageable

Note: VIF = Variance Inflation Factor; BP = Breusch-Pagan; S-W = Shapiro-Wilk. All tests conducted in IBM SPSS Statistics 27.

Table 9 summarizes the ANOVA results for all outcome variables across farm-size categories.

Table 9. Summary of one-way ANOVA results comparing outcome variables across farm-size categories.

Outcome Variable	ANOVA Result	Effect Size	Post-hoc (Tukey HSD)	Direction
Carbon footprint (kg CO_2-eq/acre)	$F(2, 197) = 3.42$, $p = 0.034$*	$\eta^2 = 0.033$	Small vs. Large $p = 0.029$	Small < Medium < Large
Carbon footprint (kg CO_2-eq/kg output)	$F(2, 197) = 1.87$, $p = 0.157$	—	—	No significant difference
Water-use efficiency	$F(2, 197) = 8.91$, $p < 0.001$***	$\eta^2 = 0.083$	All pairs $p < 0.05$ (Tukey)	Small > Medium > Large
Water footprint (m^3/kg)	$F(2, 197) = 0.14$, $p = 0.871$	—	—	No significant difference

Note: * $p < 0.05$; *** $p < 0.001$. Post-hoc comparisons by Tukey HSD. η^2 = partial eta-squared (effect size). CF = carbon footprint; WUE = water-use efficiency; WF = water footprint.

5. Discussion

Carbon and Water Footprint Findings in Regional Perspective

The Vehari CF estimates (full-sample mean: 613.2 kg CO_2-eq/acre) sit within the mid-range of 400–780 kg CO_2-eq/acre reported across comparable cotton studies from Pakistan, India, Iran, and Australia (Table 3). The finding that electricity rather than fertilizer is the single largest emission source across all farm-size categories in Vehari is consistent with Pakistan's continued reliance on a thermal-heavy national grid for tube-well pumping throughout Punjab. This implies that the carbon intensity of cotton production in Vehari is, in part, a downstream function of national electricity-generation policy rather than solely of on-farm management decisions. This linkage has direct policy implications: grid decarbonization through the expansion of renewable energy, or on-farm solarization of tube wells, would reduce cotton CF even in the absence of changes in irrigation behavior, a co-benefit that should be explicitly incorporated into national CSA programming.

The finding that medium farmers achieved the highest per-kg CF (0.738 kg CO_2-eq/kg) despite neither the highest per-acre CF nor the highest input intensity deserves specific attention. This outcome reflects the interaction of two factors: medium farmers' particularly high diesel consumption per acre (235.75 kg CO_2-eq/acre, 36% of their total the highest diesel share of any category) combined with their intermediate yields. Medium farmers appear to rely more heavily on hired diesel-powered machinery (e.g., tractors for tillage and pesticide application) than either small farmers (who use electric tube wells and more manual labor) or large farmers (who more frequently own their machinery, achieving greater operational efficiency per unit of output). This mechanization transition effect, where medium farms bear the costs of mechanization adoption without yet realizing the full-scale efficiencies of large farms, is consistent with the Schultz-type hypothesis of inefficient transition during agricultural modernization (Schultz, 1964) and is a factor that extension programs should specifically address through group mechanization schemes or custom hiring centers targeted at medium-scale farmers.

The finding that WUE declines with farm size (from 0.805 for small to 0.688 for large), while per-kg WF remains statistically indistinguishable across categories, has critical policy implications that would be missed by relying on WF alone as the irrigation management indicator. The gap between large farmers' WUE (0.688) and the already-demonstrated best practice among small farmers in the same district (0.805) represents a 17 percentage-point improvement potential broadly consistent with, though at the lower end of, the 46–54% improvement in national cotton WUE estimated as achievable through improved irrigation management (Jamil et al., 2021). Given that Pakistan's water resource assessments have repeatedly flagged the country's approach toward acute water scarcity (Watto & Mugera, 2015), and that the PRIAT project explicitly targets improvements in on-farm water productivity (World Bank, 2024), the WUE results, rather than WF alone, should anchor the targeting of water-productivity programs toward larger cotton holdings in the Vehari area.

Interpretation of Regression Results

The positive association between farm size and CF ($\beta = 0.315$, $p < 0.001$) reflects the structural reality that larger farms apply greater absolute input volumes, generating proportionally higher total emissions per acre, a finding consistent with Imran et al. (2018) for Muzaffargarh cotton. The positive association between education and CF ($\beta = 0.160$, $p = 0.019$) may initially appear counterintuitive, as educated farmers might be expected to adopt more resource-efficient practices. However, this finding is consistent with empirical evidence that, in the early stages of agricultural modernization, education is positively correlated with the adoption of mechanized inputs (electric tube wells, tractors, and chemical fertilizers) rather than with input minimization per se (Ali & Byerlee, 1991). More educated farmers in Vehari appear to be higher input-intensity farmers, not lower, a pattern that suggests extension services need to complement literacy-based knowledge with specific resource-efficiency messages targeted at better-educated, higher-adoption-rate farmers. This interpretation is consistent with Imran et al.'s (2022) finding that CSA adoption in Punjab is higher among more educated farmers but does not automatically translate into lower emissions without specific resource-efficiency training.

The negative association between household income and CF ($\beta = -0.206$, $p = 0.003$) suggests that, holding farm size constant, households with more diversified or off-farm income apply somewhat less carbon-intensive input combinations on their cotton land. One plausible mechanism is that income diversification reduces the pressure for intensive monocrop maximization as a primary livelihood strategy, allowing households to substitute off-farm earnings for marginal input expenditure. A second, complementary mechanism is that wealthier households may be better positioned to invest in energy-efficient technologies (e.g., submersible pumps, higher-efficiency motors) that reduce per-unit electricity consumption. These interpretations remain speculative in the absence of richer panel data; future longitudinal work should explicitly test income diversification pathways.

The modest R^2 (0.148) indicates that a substantial share of variation in farm-level CF remains unexplained by the three socio-economic variables available. This is expected: farm-level CF is also a function of irrigation source type (canal vs. tube well vs. surface drainage), soil type, machinery vintage, tenancy status, and specific variety choices not available in the current survey instrument. The adjusted R^2 of 0.112 is nonetheless consistent with the explanatory range reported in comparable farm-level CF regression studies in South Asia (Imran et al., 2018; Pandey et al., 2011), and the diagnostic tests confirm that the low R^2 reflects genuine omitted heterogeneity rather than model misspecification.

Limitations

Several limitations qualify these findings. First, the CF estimation relies on published generalized emission coefficients (Table 1) rather than locally measured emission factors for Pakistan's specific grid mix, fertilizer processes, or diesel quality. While this is the standard approach in farm-level CF studies globally (Lal, 2004), it introduces uncertainty into absolute footprint levels; relative comparisons across farm-size categories within the study are more reliable than cross-country absolute comparisons. Second, the regression model explains only 14.8% of CF variance, indicating important omitted variables including irrigation source type, soil type, machinery vintage, and credit access that future work should incorporate. Third, the study employs a cross-sectional design; panel data would be required to establish causal mechanisms in the observed associations. Fourth, WUE and WF comparators in Table 6 are not all methodologically identical (see Section 3 notes); Table 6 should be read as indicative contextual benchmarking rather than strict like-for-like comparison. Fifth, the sample was drawn from three tehsils of a single district, and findings may not be directly generalizable to other cotton-growing districts with different canal-irrigation configurations, energy-source mixes, or farm-size distributions.

6. Conclusion and Policy Recommendations

This study has quantified the CF, WF, and WUE of smallholder cotton production across small, medium, and large farm-size categories in District Vehari, Punjab, using primary survey data from 200 farm households, and examined the socio-economic determinants of CF using OLS regression with comprehensive diagnostic testing. Two core findings stand out. First, per-acre CF increases significantly with farm size and is overwhelmingly concentrated in electricity, diesel, and urea, which jointly account for 88–89% of total CF across all categories; per-kilogram CF is, however, not statistically different across farm-size categories. Second, WUE falls significantly with farm size, even though per-kg WF does not, indicating that larger farms have the greatest unrealized water-saving potential through improved irrigation scheduling, a pattern statistically confirmed at the 0.1% significance level. These findings, read alongside the accelerating climate and water-scarcity pressures documented in Section 2, support a policy agenda that targets resource-use efficiency directly rather than relying on farm size as a proxy for environmental performance.

The following policy instruments, differentiated by farm-size category and aligned with Pakistan's National Climate Change Policy (2021), National Water Policy (2018), Agriculture Transformation Plan (2022), and the PRIAT project, are recommended:

- Solar tube-well conversion program, priority-targeted at large farms. Since electricity and diesel jointly account for approximately 74–87% of cotton's per-acre CF, and since large farms have both higher absolute energy-related emissions and significantly lower WUE, a subsidized solar tube-well conversion program targeted at large cotton holdings in Vehari would simultaneously reduce CF and improve WUE per investment rupee. Pakistan's Kissan Roshan Package and the Alternative Energy Development Board's net-metering framework provide existing institutional channels for such targeting. Provincial CSA programs should explicitly incorporate farm-size thresholds in eligibility criteria.
- Soil-test-based, split-dose urea application, delivered through farm-size-differentiated extension. Because urea is the single largest fertilizer-related emission source across all farm-size categories, contributing 12–14% of total CF, extension programs should promote soil-test-based, split-dose nitrogen application calibrated to actual crop requirement. Critically, given the positive education-CF relationship identified in the regression, extension messaging should be specifically tailored for the more educated, higher-mechanization medium and large farmer segments, where the combination of higher input intensity and available surplus income creates the greatest leverage for resource-efficiency messaging.
- Precision irrigation incentive scheme with volumetric pricing piloted on large holdings. The statistically significant WUE gap across farm-size categories, with large farmers over-irrigating by a margin of roughly 43% above the small-farm benchmark, justifies a targeted pilot of volumetric or tiered tube-well electricity pricing on large cotton holdings. Flat-rate tariffs currently provide no marginal disincentive to over-irrigation; even modest volumetric price signals would increase the private cost of over-application and encourage adoption of precision irrigation technologies (tensiometers, irrigation scheduling apps) within reach of large farms' capital base.
- Carbon credit and payment for ecosystem services (PES) schemes for small farmers. Small farmers in Vehari already demonstrate significantly lower per-acre CF (554.6 kg CO_2-eq/acre) and significantly higher WUE (0.805) than the rest of the sample. These farmers represent a natural baseline for voluntary carbon market

| https://doi.org/10.66529/agripat.2026.2.3.96

participation: a carbon-labeling and PES scheme that rewards existing low-intensity small farmers and incentivizes medium and large farms to converge toward their practices, would mobilize private climate finance alongside public extension investment. Pilot frameworks for agricultural carbon credits are already under development in Pakistan's National Carbon Market through the Climate Change Act 2017; the Vehari baseline data presented in this study could directly inform the setting of farm-category-specific emission benchmarks.

- Benchmarked WUE targets large farms in extension contracts. Given independent estimates that national cotton WUE could realistically improve by 46–54% (Jamil et al., 2021) and given that large farmers in this study already lag significantly behind small farmers demonstrated WUE, provincial water management extension programs should adopt explicit, monitorable WUE targets for large farmers rather than uniform district-wide targets. These targets should be incorporated into the farmer extension service agreements now being piloted under the PRIAT project.

Implementing this agenda will require inter-institutional coordination among agricultural extension departments, electricity distribution companies (DISCOs), provincial irrigation authorities, fertilizer-sector regulators, and the Climate Change Division. The convergence identified in this study between the inputs most responsible for cotton's CF (electricity, diesel, urea) and the farm-size-specific WUE gaps documented here suggests that a single, well-targeted package of irrigation and energy interventions aimed at larger cotton holdings could deliver mutually reinforcing emissions and water benefits, making such investment a practical, near-term priority for provincial CSA programming in Pakistan's cotton belt. Future research should extend this analysis to panel data, incorporate additional variables (irrigation source, machinery vintage, tenancy), and assess the cost-effectiveness of the proposed policy instruments through controlled field experiments.

References

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration: Guidelines for computing crop water requirements (FAO Irrigation and Drainage Paper No. 56). Food and Agriculture Organization of the United Nations.

Browne, T., Notaro, S., & McDonnell, K. (2011). The greenhouse gas emissions of agriculture: An overview of methods and findings. Journal of Cleaner Production, 19(11), 1207–1214. https://doi.org/10.1016/j.jclepro.2011.02.001

Chapagain, A. K., & Hoekstra, A. Y. (2004). Water footprints of nations (Value of Water Research Report Series No. 16). UNESCO-IHE Institute for Water Education.

Chapagain, A. K., Hoekstra, A. Y., Savenije, H. H. G., & Gautam, R. (2006). The water footprint of cotton consumption: An assessment of the impact of worldwide consumption of cotton products on the water resources in the cotton producing countries. Ecological Economics, 60(1), 186–203. https://doi.org/10.1016/j.ecolecon.2005.11.027

Cochran, W. G. (1977). Sampling techniques (3rd ed.). John Wiley & Sons.

Dyer, J. A., & Desjardins, R. L. (2003). The impact of farm machinery management on greenhouse gas emissions from Canadian agriculture. Journal of Sustainable Agriculture, 22(3), 59–74. https://doi.org/10.1300/J064v22n03_07

Food and Agriculture Organization. (2010). CROPWAT 8.0 model. FAO Land and Water Division.

Garcia, C. A. (2011). Life-cycle greenhouse gas emissions of electricity generation in developing countries: A coefficient approach. Energy Policy, 39(9), 5557–5566. https://doi.org/10.1016/j.enpol.2011.05.001

Germanwatch. (2025). Global Climate Risk Index 2025. Germanwatch e.V.

Government of Pakistan. (2024). Pakistan Economic Survey 2023–24. Ministry of Finance, Finance Division.

Hillier, J., Walter, C., Malin, D., Garcia-Suarez, T., Mila-i-Canals, L., & Smith, P. (2013). A farm-focused calculator for emissions from crop and livestock production. Environmental Modelling & Software, 26(9), 1070–1078. https://doi.org/10.1016/j.envsoft.2011.03.014

Hoekstra, A. Y., Chapagain, A. K., Aldaya, M. M., & Mekonnen, M. M. (2011). The water footprint assessment manual: Setting the global standard. Earthscan.

Hoekstra, A. Y., & Hung, P. Q. (2002). Virtual water trade: A quantification of virtual water flows between nations in relation to international crop trade (Value of Water Research Report Series No. 11). IHE Delft.

Imran, M. A., Ali, A., Ashfaq, M., Hassan, S., Culas, R., & Ma, C. (2018). Impact of climate smart agriculture (CSA) practices on cotton production and livelihood of farmers in Punjab, Pakistan. Sustainability, 10(6), 2101. https://doi.org/10.3390/su10062101

Imran, M. A., Ali, A., Culas, R. J., Ashfaq, M., Baig, I. A., Nasir, S., & Hashmi, A. H. (2022). Sustainability and efficiency analysis with respect to adoption of climate-smart agriculture (CSA) in Pakistan: A group-wise comparison of adopters and conventional farmers. Sustainability, 14(2), 1009. https://doi.org/10.3390/su14021009

Intergovernmental Panel on Climate Change. (2007). Climate change 2007: The physical science basis (Contribution of Working Group I to the Fourth Assessment Report). Cambridge University Press.

Intergovernmental Panel on Climate Change. (2021). Climate change 2021: The physical science basis (Contribution of Working Group I to the Sixth Assessment Report). Cambridge University Press. https://doi.org/10.1017/9781009157896

Jamil, I., Jun, W., Mughal, B., Waheed, J., Hussain, H., & Waseem, M. (2021). Agricultural innovation: A comparative analysis of economic benefits gained by farmers under climate resilient and conventional agricultural practices. Land Use Policy, 108, Article 105581. https://doi.org/10.1016/j.landusepol.2021.105581

Kaur, S., Sidana, B. K., Kaur, S., & Biswas, A. (2025). Carbon footprint reduction in Punjab agriculture: Analyzing impacts and strategies in major crop rotations. Journal of Agriculture and Food Research, 21, Article 101574. https://doi.org/10.1016/j.jafr.2025.101574

Khan, Y., & Ali, Y. (2024). Analysis of water footprint and sustainability of the cotton supply chain in Pakistan. Water Conservation Science and Engineering, 9, 18. https://doi.org/10.1007/s41101-024-00252-0

Komleh, S. P., Rafiee, S., Jafari, A., & Mousavi-Avval, S. H. (2012). Energy use and greenhouse gas emissions of cotton production systems: A case study in Iran. Journal of Cleaner Production, 35, 116–122. https://doi.org/10.1016/j.jclepro.2012.05.026

Lal, R. (2004). Carbon emission from farm operations. Environment International, 30(7), 981–990. https://doi.org/10.1016/j.envint.2004.03.005

Makhdum, A. H., Khan, H. N., & Ahmad, S. (2018). Reducing cotton footprints through implementation of better management practices in cotton production: A step towards better cotton initiative. In Proceedings of the Fifth Meeting of the Asian Cotton Research and Development Network (pp. 1–18). International Cotton Advisory Committee.

Maraseni, T. N., Cockfield, G., Maroulis, J., & Chen, G. (2010). An assessment of greenhouse gas emissions from the Australian cotton industry. Journal of Environmental Science and Health, Part A, 45(4), 379–387. https://doi.org/10.1080/10934520903540116

Ministry of National Food Security and Research. (2025). Agriculture sector performance review, fiscal year 2024–25. Government of Pakistan.

Pandey, D., Agrawal, M., & Pandey, J. S. (2011). Carbon footprint: Current methods of estimation. Environmental Monitoring and Assessment, 178(1–4), 135–160. https://doi.org/10.1007/s10661-010-1678-y

Pathak, H., & Wassmann, R. (2007). Introducing greenhouse gas mitigation as a development objective in rice-based agriculture: I. Generation of technical coefficients. Agricultural Systems, 94(3), 807–825. https://doi.org/10.1016/j.agsy.2006.11.014

Schultz, T. W. (1964). Transforming traditional agriculture. Yale University Press.

United States Department of Agriculture, Foreign Agricultural Service. (2025). Cotton and products annual: Pakistan (GAIN Report No. PK2025-0002). USDA FAS.

Visser, W. P., Whish, J., & Yeates, S. (2014). Cotton industry greenhouse gas emissions and water use in northern New South Wales, Australia. Crop and Pasture Science, 65(11), 1183–1192. https://doi.org/10.1071/CP13413

Watto, M. A., & Mugera, A. W. (2015). Econometric estimation of groundwater irrigation efficiency of cotton cultivation farms in Pakistan. Journal of Hydrology: Regional Studies, 4, 193–211. https://doi.org/10.1016/j.ejrh.2015.05.012

Wiedmann, T., & Minx, J. (2008). A definition of carbon footprint. In C. C. Pertsova (Ed.), Ecological economics research trends (pp. 1–11). Nova Science Publishers.

World Bank. (2023). Pakistan floods 2022: Post-disaster needs assessment. World Bank Group.

World Bank. (2024). Punjab Resilient and Inclusive Agriculture Transformation Project: Project appraisal document (Report No. PAD4876). World Bank Group.

Declarations

Ethical Considerations: Informed verbal consent was obtained from all participants.

Conflict of Interest: The authors declare no conflict of interest.

Data Availability: The anonymized dataset supporting this study is available from the corresponding author upon reasonable request.

Author Contributions: Farooq - conceptualization, writing (original draft), review & editing. Javaid, Mateen & Irfan – writing (review & editing),