Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 9, No. 6, December, 2025

The Impact of Climate-Smart Technology Adoption on Agricultural Productivity and Environmental Sustainability

Farkhod Karakulov [1], Bakhtiyor Menglikulov [2], Abror Mamasadikov [3], Shaknoza Kholbutaeva [2], Abdukholik Mukhtorov [4], Gulshan Abdulkhaeva [5], Dilshoda Gafurova [6], Sodik Ruziyev [2], Sultanbek Ablatdinov [2], Akmal Durmanov [7, 8*]

[1] Graduate School of Business and Entrepreneurship under the Cabinet of Ministers of the Republic of Uzbekistan, Uzbekistan.

[2] Department of Financial Analysis and Auditing, Tashkent State University of Economics, Tashkent, Uzbekistan.

[3] Tashkent Institute of Irrigation and Agricultural Mechanization Engineers (TIIAME) - National Research University, Tashkent 100000, Uzbekistan.

[4] International Centre for Food and Agriculture Strategic Development and Research under the Ministry of Agriculture of the Republic of Uzbekistan (I-SCAD), Tashkent 100140, Uzbekistan.

[5] Department of Tourism and Hotel Management, Termez State University, Termez, Uzbekistan.

[6] Department of Management and Marketing, Kimyo International University, Tashkent, Uzbekistan.

[7] Department of Corporate Economics and Management, Tashkent State University of Economics, Tashkent, Uzbekistan.

[8] Department of Economics, Alfraganus University, Tashkent, Uzbekistan.

Abstract

This study provides an empirical assessment of emerging opportunities and offers a conceptual framework for understanding the potential impacts of climate-smart agriculture (CSA) adoption on agricultural productivity and environmental sustainability. Focusing on Uzbekistan, the research employs quantitative analysis of farm-level data, adoption gradient modeling, and return-on-investment (ROI) estimation to examine how CSA technologies influence key farm-level outcomes, including yields, income, resource-use efficiency (RUE), soil erosion, and water quality under world constraints. In cotton-wheat systems, the usage of six or more CSA is associated with a 71% increase in farm income, a 43% rise in crop yields, and a 48% improvement in resource-use efficiency (RUE), compared to farms with low levels of CSA usage. Fertilizer micro-dosing is associated with an average increase in cotton yields of 245.8 kg ha^{-1} yr^{-1} and delivers a ROI of 456%. Multivariate regression models account for 57.3% of the variation in yield and 61.8% in farm income, underscoring the explanatory power of CSA adoption patterns. Comparative analyses demonstrate that organic matter-based practices consistently outperform capital-intensive alternatives in both economic and environmental terms. The methodological approach integrates monitoring, reporting, and verification (MRV) indicators, payback period estimations, and threshold analyses tailored to risk-sensitive smallholder contexts. The findings provide robust empirical support for evidence-informed CSA policy formulation, including the design of targeted subsidies, extension services, and investment strategies in Uzbekistan. By reconciling global CSA implementation paradigms with localized constraints, the study generates scalable and empirically validated approaches, offering methodological relevance for analogous agroecological and institutional contexts.

Keywords:

Climate-Smart Agriculture (CSA);
Agricultural Productivity;
Environmental Sustainability;
Fergana Valley;
Fertilizer Micro-Dosing;
Farm Income;
Irrigated Agroecosystems;
Resource Use Efficiency (RUE);
Soil Conservation.

Article History:

Received:	11	August	2025
Revised:	10	November	2025
Accepted:	15	November	2025
Published:	01	December	2025

1- Introduction

Accelerating climate change increases the vulnerability of agricultural and food systems. The sector faces growing threats from extreme heat, prolonged droughts, and erratic precipitation patterns while simultaneously contributing to

* **CONTACT**: akmal.s.durmanov@gmail.com

DOI: http://dx.doi.org/10.28991/ESJ-2025-09-06-012

anthropogenic greenhouse gas emissions, primarily through the use of synthetic fertilizers and associated soil degradation processes. This dual challenge has become a central focus in interdisciplinary research [1-7], framed as an imperative for transitioning toward CSA: an integrated architecture of technological and management solutions designed to increase productivity, strengthen resilience to climate stressors, and reduce carbon footprints. Comprehensive assessments by the Intergovernmental Panel on Climate Change (IPCC) in its Sixth Assessment Report (AR6) systematize data on emissions from agriculture, forestry, and other land use (AFOLU). AFOLU accounts for approximately 13-21% of global greenhouse gas emissions, with soil nutrient management identified as a key driver of nitrous oxide (N_2O) emissions [8].

These challenges are intensified by water scarcity, declining water quality, widespread soil salinization, and institutional constraints in water governance systems in countries with irrigated agriculture [9, 10]. Given these pressures, the agricultural sector plays a vital role in ensuring food security, advancing sustainable development principles, and mitigating the impacts of climate change [11-13]. Achieving these objectives requires a comprehensive, coordinated, and multilevel approach involving public authorities, the scientific community, and agricultural producers [14-16].

CSA represents an integrated approach designed to enhance sustainable agricultural productivity and incomes while concurrently building adaptive capacity to climate-related risks and mitigating anthropogenic greenhouse gas emissions within resource constraints and through standardized performance metrics [17, 18]. In irrigated farming systems, CSA is operationalized via synergistic packages of technological and institutional innovations metrics [19]. These include precision agriculture techniques leveraging geospatial tools and remote sensing to optimize field-level interventions, alongside digital monitoring infrastructures that employ sensor arrays to track soil moisture, water fluxes, and energy dynamics in real time. Advanced decision-support systems, increasingly powered by artificial intelligence, enable dynamic irrigation scheduling, nutrient optimization, and crop protection tailored to evolving climatic and biophysical conditions. Complementary irrigation strategies refine water application through deficit irrigation, evapotranspiration-based scheduling, and pressure regulation, enhancing water-use efficiency and conserving energy [20, 21]. At broader hydrological scales, CSA encompasses salinity management and coordinated surface-groundwater use to preserve resource integrity. Biologically grounded practices, including stress-resilient genotypes, agroforestry, conservation tillage, and soil organic carbon restoration, further reinforce system resilience. To address climate and market uncertainties, CSA integrates risk management frameworks such as index-based insurance, livelihood diversification, cooperative resource sharing, and digitally enabled service platforms, thereby fostering ecological and socio-economic robustness across agricultural landscapes [22-27].

The achievement of CSA objectives is verified through a measurement, reporting, and verification approach centered on key performance indicators: crop yield and profitability; resilience and risk exposure indices; water productivity (kg of output per m^3 of water); water balance and quality (including salinity dynamics); carbon and nitrogen footprints (CO_2-eq, N_2O, CH_4); biodiversity; and soil health. The CSA architecture relies on institutional compatibility (water rights, tariff and regulatory provisions, data standards, and access to finance and insurance) and operates across multiple scales, from field and farm to irrigation systems and watershed levels. Crucially, it requires context-specific adaptation to local agro-climatic and socio-economic conditions [28-31].

The integration of CSA practices into production agro-systems directly aligning with the United Nations Sustainable Development Goals (SDGs), particularly Zero Hunger (SDG 2) and Climate Action (SDG 13) [32]. Contemporary meta-analyses and thematic scientific reviews consistently report that, on average, CSA practices triple crop yields and household incomes, double farm-level resource-use efficiency, and significantly improve household resilience. However, trade-offs exist between maximizing total productivity, saving water, and implementing costs [14, 33, 34]. By adopting CSA, nations can work toward achieving multiple (SDG), including SDG 1 (no poverty), SDG 2 (zero hunger), SDG 7 (affordable and clean energy), and SDG 13 (climate action) [35, 36].

Despite a growing body of research, institutional and financial constraints have hindered the widespread scaling of CSA. Key barriers include weak coordination among government programs; subsidies not linked to climate outcomes; high transaction costs for smallholder farms; limited access to finance; and a lack of standardized measurement, reporting, and verification (MRV) data at the local level [10, 14]. Scientific evidence indicates that CSA adoption is not only multi-level but also shaped by a specific configuration of determinants across the entire value chain (from farm production to processing and retail), with reproducible drivers at each stage [37-41]. Significant farm-level factors include farmer education, agricultural experience, labor availability, farm size, and mechanization. At the technological level, enabling conditions include digital infrastructure, access to precision agriculture services, and technology compatibility [42-44]. Access to credit and insurance, as well as subsidy structures, influence the financial level. The intensity of extension services, participation in farmer groups or cooperatives, and engagement with digital platforms play critical roles at the informational level [45-47]. Contract farming arrangements with processors or retailers, and price premiums for quality or sustainability enhance market adoption. Finally, program stability and policy coherence are essential at institutional and policy levels.

While financial constraints undeniably influence the adoption of CSA technologies, empirical findings suggest that economic considerations alone do not adequately capture the complexity of adoption itself. In particular, the limited uptake of technically sound yet underutilized practices, such as cover cropping and solar-powered irrigation, reflects the salience of non-financial barriers operating at the cultural, cognitive, and institutional levels.

Solar irrigation technologies, which are theoretically attractive because of their long-term economic and environmental benefits, face a parallel set of obstacles. Many farmers reported a limited technical understanding of system design, maintenance, and payback mechanisms, contributing to perceived risk and reluctance. This knowledge gap was further exacerbated by the absence of localized demonstration plots and credible peer adoption examples, which, according to diffusion of innovation theory [48], are critical for reducing uncertainty and facilitating social learning. As a result, even farmers with access to capital expressed hesitation, reflecting not just informational constraints but deeper cognitive inertia and status quo bias.

Institutional constraints reinforce these dynamics, and this study reveals systemic gaps in the availability of skilled extension personnel capable of supporting CSA diffusion, particularly for advanced or non-traditional technologies. Bureaucratic rigidity in the administration of subsidies and credit programs imposes transaction costs that disproportionately affect smallholders. These structural deficiencies reduce the accessibility and perceived attainability of CSA interventions even when they are agronomically and economically viable.

These findings highlight the need for a more holistic, system-oriented approach to CSA promotion. Interventions focused solely on financial incentives are unlikely to achieve widespread and sustained adoption without parallel efforts to enhance technical capacity, address cultural misalignment, or reform institutional delivery mechanisms. Understanding CSA adoption as a socially embedded, cognitively mediated process underscores the importance of integrating behavioral insights, peer-based knowledge transfer, and co-designed demonstration efforts [49]. Future CSA strategies must therefore recognize farmers not merely as economic agents but as situated decision-makers operating within specific cultural, informational, and institutional ecosystems.

Access to credit accelerates CSA adoption, whereas high upfront costs and climatic uncertainty are major barriers. For example, in Pakistan, information access, farm size, and cooperative membership were found to be decisive, and CSA adoption was associated with improved household food security and higher incomes [50]. In Botswana, the need to simultaneously adopt complementary practices (i.e., crop rotation, legume diversification, improved seed varieties, and optimized fertilizer application) increases the importance of farmer education, access to quality seeds, and credit [51]. In Bangladesh, implementation costs, skill shortages, and insufficient technical support services are the key constraints for using CSA [52].

In Central Asian countries, particularly Uzbekistan, irrigated agriculture based on cotton-wheat crop rotations faces chronic water stress, soil salinization, and high climatic variability. The agricultural sector remains a significant contributor to employment and GDP [9-26]. Climate change poses a serious threat to Uzbekistan's agricultural sector, a key economic driver that accounts for approximately 25% of the country's GDP [53-56]. Agriculture is especially vulnerable, as nearly half of the rural population (49.3%) depends directly or indirectly on this sector for their livelihoods. As expected, by 2050, the total river flow in the Amu Darya basin in Karakalpakstan will decline by an additional 35% by 2050, while the irrigation water demand is expected to increase by 25%. Recent studies reports have documented declining per capita water availability and increasing frequency of droughts, thereby undermining the resilience of irrigation systems and worsening food security risks [9, 27]. The transition to CSA is increasingly being regarded as a necessary strategy for sustaining agricultural productivity and enhancing adaptive capacity under these conditions. This shift is now widely recognized as a strategic priority within the national climate and food security policy approaches [10].

However, despite the growing body of evidence, significant gaps remain in understanding the quantifiable impacts of specific CSA technology adoption on key agricultural performance indicators [30, 31]. Although comprehensive reviews have highlighted the potential of various CSA practices, empirical studies that quantify these relationships are limited. Most existing research has focused on adoption patterns and barriers rather than measuring concrete outcomes, such as yield gains, income changes, and resource use efficiency (RUE) [34, 57, 58]. Furthermore, most studies have been conducted in well-documented agricultural regions, including Sub-Saharan Africa, South Asia, and Europe, leaving substantial knowledge gaps regarding the effectiveness of CSA in Central Asian contexts. This is particularly evident in Uzbekistan, where agricultural systems are characterized by intensive irrigation, cotton-dominated cropping systems, and a unique combination of water scarcity, soil salinization, and high climate variability, which may influence the performance of CSA technologies differently compared to other agroecological zones [59-61].

Starting in 2020, Uzbekistan abolished state procurement and cotton quotas, and in 2021, it abolished fixed-state procurement prices and wheat volumes. Further regulation is primarily conducted through market-contract mechanisms (including clusters) [62]. Despite the formal abolition of state cotton quotas in 2020 and ongoing liberalization efforts in the wheat sector, Uzbekistan's agricultural landscape continues to exhibit strong centralized control features.

Approximately 70% of the arable land remains de facto allocated to cotton and wheat production through state-led irrigation priorities, land-use planning, and procurement mechanisms. This hybrid governance model is characterized by the coexistence of formal market liberalization and persistent administrative influence, which shapes the institutional feasibility of any reform agenda [63]. Accordingly, the recommendations presented in this study are formulated within a gradualist framework to align policy change with existing structural constraints while facilitating a transition toward a more market-oriented and diversified agricultural economy.

Uzbekistan represents a distinct agricultural research field that has not been adequately addressed in existing literature. The country's continental arid climate, dependence on irrigated farming, and dominant cotton-wheat rotation system present both challenges and opportunities for CSA implementation. Agriculture remains a major employer and contributes significantly to the national economy; however, it faces mounting pressure from declining water availability, deteriorating soil quality, and increasing climatic uncertainty [64]. Conventional farming practices have contributed to reduced soil fertility, inefficient water use, and stagnating crop yields, highlighting the urgent need for sustainable and resource-efficient technological interventions [65].

Although international studies have demonstrated the potential benefits of various CSA practices [43, 66], the external validity of these findings in Uzbekistan remains uncertain because of the country's distinct agroecological and socioeconomic contexts. This uncertainty impedes the design of targeted interventions and efficient resource allocation strategies aimed to promote widespread CSA adoption and improve agricultural productivity and environmental performance [67]. Although the pool of climate-smart agriculture CSA-related literature is rather rich, there are certain evidence gaps, such as regarding irrigated agro-ecosystems in Central Asia, particularly Uzbekistan's Fergana Valley. Most quantitative CSA studies and meta-analyses synthesize evidence from rainfed systems in sub-Saharan Africa and Southeast Asia [68-70]. The external validity of intensively irrigated, salinity-prone landscapes with pump-dependent delivery remains largely untested, leaving policymakers uncertain about the expected yield, profitability, and environmental effects under binding water, energy, and salinity constraints. Prior studies mostly emphasize adoption determinants and descriptive project outcomes; only a small percentage of those studies cover farm-level, jointly measured productivity (yields, income, resource-use efficiency), and environmental indicators (soil erosion and water quality) using a coherent MRV framework that can provide cost-effective scaling [71-74]. Evidence on bundled CSA adoption and adoption intensity (dose-response) effects is scarce, and cross-sectional designs that do not separate the selection of more efficient producers from technology effects often limit causal interpretation. Consequently, the contribution of specific practices (e.g., fertilizer micro-dosing, organic amendments, cover cropping, and solar irrigation) within realistic technology packages is under quantified. Few studies report technology-specific returns on investment, payback periods, and downside risk under irrigated conditions or evaluate financing frictions relevant to smallholders (capital costs, learning-by-doing, and adverse-season shocks) [75-77]. This limits the design of the targeted subsidies, credit lines, and extension priorities.

The present study uses primary data to address the identified gaps by rigorously evaluating quantitative, farm-level estimates of individual and bundled CSA effects on yields, income, resource-use efficiency, soil erosion, and water quality, adoption-intensity practice gradients that reveal synergistic gains, and technology-specific return on investment (ROI) and payback analyses under uncertainty.

This approach is grounded in the scientific rationale that evidence-based assessment of CSA practices using robust empirical methods under real-world farm conditions remains crucial for validating global sustainability claims in diverse agro-ecological settings. By focusing on both individual and bundled practices, the study captures nonlinear interactions and context-specific synergies often overlooked in global models or meta-analyses. Evaluating adoption gradients and ROI under uncertainty provides a practical lens to understand the economic rationality behind farmers' decisions, which is essential for designing effective interventions.

The analysis is embedded in Uzbekistan's environment, directly addressing the transferability of global CSA claims to irrigated Central Asian systems, including crop yield, farm income, resource-use efficiency, soil conservation, and water quality. The resulting policy-relevant evidence is intended to support decision making and inform the design of scalable extension programs across Central Asian agricultural contexts.

2- Methodology

2-1- Research Design

This study is situated within a post-positivist epistemological paradigm, which acknowledges both the complexity and the inherently partial observability of real-world agricultural systems. Within this framework, the research design prioritizes empirical rigor while explicitly accounting for potential measurement constraints and context-specific variability. A cross-sectional survey design was employed to examine the associations between the adoption of CSA practices and key farm-level outcomes, including productivity, income, and environmental performance. To operationalize this paradigm, the study integrates multiple data sources through a mixed-methods approach, enabling a more comprehensive and contextually grounded analysis.

Data collection integrated structured farmer interviews, biophysical field measurements, and economic performance indicators, thereby enabling triangulation across the data types. This approach strengthens internal validity and enhances explanatory depth, particularly in environments in which both biophysical and socioeconomic variables interact dynamically. A cross-sectional design was selected for its methodological feasibility, cost-effectiveness, and capacity to support the simultaneous measurement of multiple constructs across a statistically representative farm sample. Importantly, the design facilitates a robust estimation of treatment-outcome relationships under explicitly defined identification assumptions. Key design features, such as stratified sampling by agroecological zones, standardized protocols, and comprehensive covariate collection, further improve analytical precision and create the foundation for applying quasi-experimental estimators (e.g., propensity score matching and regression adjustment) during analysis where appropriate. This design is particularly well-suited for assessing both the marginal effects of individual CSA technologies and the synergistic effects of bundled adoption, while remaining sensitive to the diversity of farm-level conditions in irrigated agroecosystems in Central Asia. Therefore, direct extrapolation of these findings to intensively irrigated agro-landscapes requires caution and further empirical validation.

First of all, The Uzbek agricultural sector exhibits structural characteristics that directly influence the economic and technological feasibility of adopting CSA. Agriculture accounts for approximately 90% of freshwater withdrawals, with an estimated 40% loss of conveyance through irrigation canals. Moreover, more than half of irrigated land is affected by primary or secondary soil salinization. The potential for extensive irrigation expansion is limited and water productivity remains low [34, 78].

Second, the agricultural system has historically been dominated by a cotton-wheat crop rotation: cotton and wheat together account for approximately 75% of land under annual crops (around 68% of the total cultivated area), with cotton occupying nearly 70% of irrigated land. This production structure creates specific price and technological incentives for CSA adoption, and significantly influences water and energy consumption patterns [79].

Third, a substantial portion of irrigation water delivery relies on pump-based systems: approximately 2.4 million hectares (approximately 56% of irrigated land) depend on electrically powered pumps (approximately 1,700 stations and over 5,000 individual pumps). This increases the energy intensity of irrigation and makes farm-level costs highly sensitive to electricity tariffs and water dispatching system efficiency [63].

Fourth, coupled with shallow groundwater tables, the degradation and aging of irrigation and drainage infrastructure increase the risk of secondary soil salinization. This issue has been documented by the Ministry of Ecology of the Republic of Uzbekistan [80] and is being addressed through ongoing World Bank-supported projects aimed at modernizing irrigation and drainage systems and improving water and energy efficiency, including the National Irrigation and Energy Efficiency Improvement Project [81].

Finally, the institutional architecture of water allocation, including water user associations, tariff schemes, and dispatching systems, shapes local rules for investments in water and nutrient management. A binomial rate system (comprising fixed and variable components) is an effective mechanism for recovering irrigation service costs and incentivizing demand-responsive water distribution in Fergana Valley [82].

Proceeding from these contextual factors, this study deliberately avoids mechanical extrapolation of average global CSA effects and explicitly tests for context-dependent heterogeneity in outcomes within Uzbekistan's irrigated agriculture. The analytical framework evaluates technology packages relevant to such systems (drip irrigation, fertigation, controlled drainage, salinity mitigation practices, cover cropping, and stress-tolerant crop varieties) in relation to key farm-level outcomes (i.e., crop yields, household income, water and resource productivity, soil health indicators, and environmental impacts). Drip irrigation and fertigation have demonstrated the potential to simultaneously reduce salt accumulation in the root zone (by tens of percent compared with surface irrigation), increase crop yields, and improve water and nitrogen use efficiency under conditions of soil salinization and water scarcity. Water-saving irrigation regimes, such as deficit irrigation (DI) and partial root-zone drying (PRD), enhance water productivity and maintain yields despite reduced water application when properly managed. These biophysical mechanisms form the basis for hypotheses regarding the positive impacts of CSA technology packages in the Uzbek context [83].

Causal effect identification distinguishes the selection of more efficient producers from the actual technological impacts. Such methodological strategies are recognized as best practices for impact evaluation and align with findings from sectoral reviews of CSA and Uzbekistan's country-specific assessments [84].

This research design facilitates a direct comparison between global CSA outcomes and the unique agroclimatic and institutional conditions of Uzbekistan. It provides actionable insights for scaling up CSA technology packages in irrigated landscapes, accounting for binding water constraints, salinization risks, energy-intensive pump-based irrigation systems, and institutional arrangements such as water user associations (WUAs) and tariff policies. The results are directly relevant to ongoing national modernization programs, including the 2020–2030 Strategy for the Development of Agriculture in Uzbekistan for 2020–2030 [85], which prioritizes agricultural transformation, climate adaptation, and the implementation of measures compatible with water and energy efficiency goals [86].

Figure 1 summarizes the research workflow employed to assess the impact of climate-smart technology adoption on agricultural productivity and environmental sustainability.

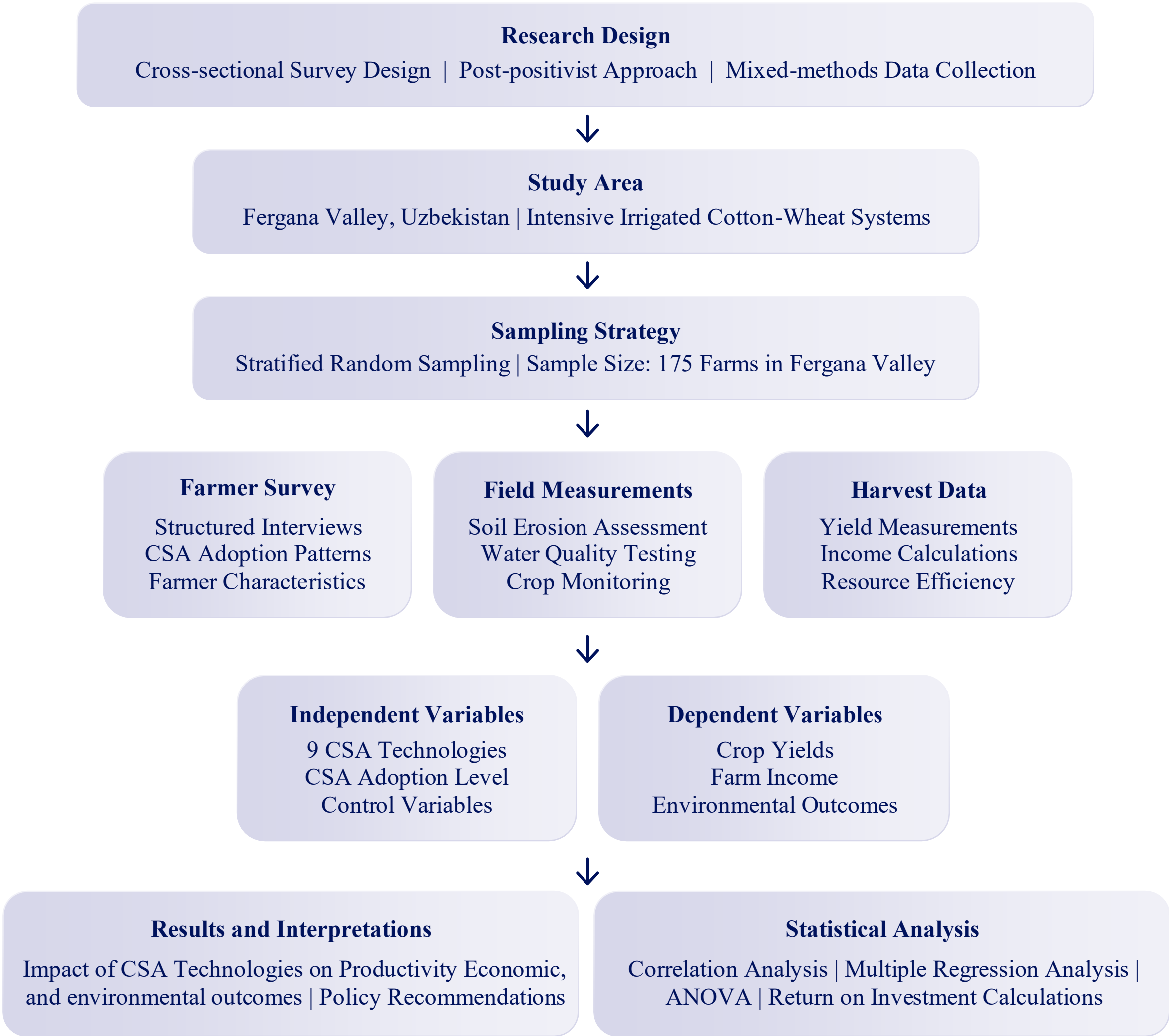

Figure 1. Structured research workflow outlining the methodological steps

2-2- Study Area

One of the largest irrigated agro-landscape systems, the part of the Fergana Valley belonging to eastern Uzbekistan, has historically specialized in intensive crop cultivation, horticulture, and livestock production. Major urban agglomerations (Fergana, Andijan, and Kokand) serve as centers of demand and logistics, where the most productive agricultural zones are concentrated. Similar production zones are located in the adjacent Andijan and Namangan districts in the Fergana region. The agro-landscape features a flat to gently undulating topography of alluvial plains, with soil textures ranging from sandy to clay loam, and an extensive network of irrigation canals and drainage systems fed by the Syr Darya River and its mountain tributaries (upstream of the Naryn River basin). The climate is continental, arid to semi-arid, and sustainable agriculture is maintained through artificial irrigation, seasonal water allocation schedules, and a dense institutional infrastructure of water user associations (WUAs). Historically, the valley has been a center for cotton and sericulture. In the post-Soviet period, the production structure diversified to include wheat, rice, maize, fruit crops (peaches, apricots, figs, and pomegranates), and vegetables, creating a demand for water-saving and resource-efficient technologies. By 2025, the Fergana region has a total of 11349 farmsteads, including 2624 medium-sized and 8725 small farms.

A stratified purposive sampling approach was applied to select three administrative districts within the Fergana region as a minimally sufficient sample representative of key sources of intra-valley heterogeneity while adhering to the logistical constraints of field operations. Stratification was based on the four a priori predefined criteria. First, districts vary in their proximity to the main water control structures and the degree of canal modernization, affecting water delivery reliability and timeliness, irrigation norms, and the need for supplemental or repeated irrigation events. Second, the study areas featured diverse combinations of soil textures (sandy loam to clay loam alluvial soils), classes of secondary salinization, and groundwater table depths. These factors influence soil permeability, sodicity, and salt stress risks, as well as crop responses to irrigation deficits and micro-dosing of fertilizer. Third, districts differ in water allocation rules and flexibility of the Water User Association (WUA) schedule (i.e., irrigation timing, crop prioritization, and conflict resolution mechanisms) that impact the adoption and effectiveness of CSA technologies. Fourth, cotton and wheat cultivation coexist in developed horticulture and vegetable farming. The combination of household farms and cluster-based agricultural enterprises creates variability in farm scale, access to machinery, and risk preferences.

The three selected districts cover a major portion of the high-productivity belt within the valley and provide a contrast across typical production conditions found in the Fergana Valley located in Uzbekistan.

The selected districts with broader valley regions were compared using available macro-level indicators (i.e., crop structure, population density, irrigation infrastructure coverage, and land reclamation indicators). Standardized mean differences (SMDs) for most variables fell within the range of 0.10–0.20 SD, which is generally considered an acceptable balance in observational study designs.

The selection of the three districts represents a justified compromise: it captures the main sources of heterogeneity (hydraulic position, drainage conditions, institutional arrangements, and production structure) while maintaining field-temporal feasibility in terms of farm accessibility, coordination with WUAs, and narrow planting and harvesting windows. Expanding to four or five districts would increase the costs and risks of seasonal misalignment, while yielding diminishing marginal informational returns. In contrast, the combination of sample balancing, weighting adjustments, and stratified estimation ensures sufficient generalizability of the findings to similar zones across the Fergana Valley, including areas in the Fergana, Andijan, and Namangan districts.

The study was conducted in the Fergana Valley of eastern Uzbekistan (Fergana Region), covering three administrative districts (Fergana, Rishton, and Bag‘dod) between 40°15′–40°45′ N and 71°30′–72°15′ E**,** encompassing approximately 1,250 km² of predominantly agricultural land. The area lies on the flat to gently sloping floor of the Fergana Depression at ≈420–580 m.a.s.l.**,** with alluvial plains under sandy-loam to clay-loam textures dominating the landscape. The continental, arid to semi-arid climate is characterized by a mean annual temperature ≈14.2 °C; precipitation ≈180–250 mm yr^{-1}, mainly in spring. Reference evapotranspiration averages ≈1,350 mm yr^{-1}, necessitating ≈800–1,200 mm of seasonal irrigation. Land tenure features numerous Dehkan (household) farms alongside larger cluster (commercial) farms; while Dehkan units constitute the majority of farm enterprises and manage a minority of land, shaping incentives for technology adoption. Figure 2 presents a multiscale location map (country context, valley extent, and district-level detail) with the georeferenced locations of the 175 sampled farms.

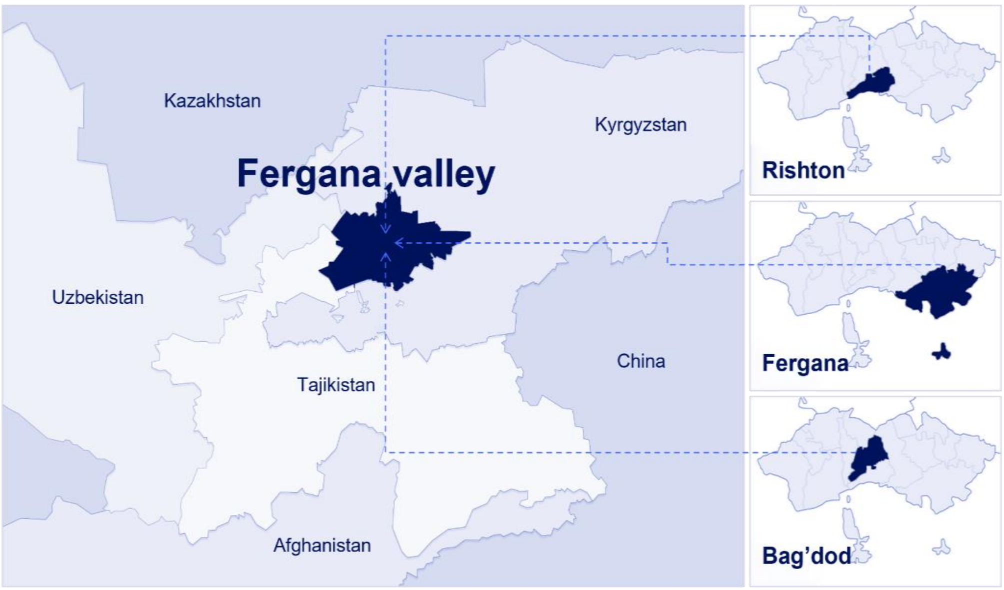

Figure 2. Study location with 175 surveyed farms in Fergana valley; Bag’dod district; Rishton district; Fergana district

In the study location, intensively irrigated farming systems dominated agriculture, with cotton (45% of the cultivated area) and wheat (25%) as primary crops, followed by vegetables (20%) and fruits (10%). Agricultural land is managed through two main farm types: Dehkan farms (private household farms), averaging 2.5 hectares, and cluster (commercial) farms, averaging 150 hectares. Dehkan farms accounted for 78% of the total farm units, but only 35% of the land was controlled. Dehkan farms represent a distinct form of agricultural organization within Central Asia’s systems, differing from typical smallholders or household farms. Established under Uzbekistan’s 1998 Law on Dehkan Farms, these individually or family operated farms function under heritable land-use rights, while all agricultural land remains state-owned [87]. Although Dehkan farms average 0.17 hectares and are legally restricted to a maximum size of 0.35 hectares for irrigated land, they differ from larger commercial farms in key institutional aspects: Dehkan farmers are not subject to state-mandated cotton and wheat quotas and have autonomy in crop selection and marketing, allowing them to sell produce at market prices [87, 88]. These farms hold lifetime and heritable tenure rights that can be transferred within families but cannot be sold to non-family members. Despite controlling less than 5% of arable land nationally, Dehkan farms contribute to approximately 60% of Uzbekistan's total agricultural output [88]. This unique institutional arrangement significantly shapes the incentives for technology adoption and distinguishes the Dehkan system from conventional private agriculture models studied in other contexts.

Historical climate data (1990–2020) indicate that rising temperatures (+0.3°C per decade) and declining precipitation (−2.5 mm per decade) contribute to increasing water stress. These trends underscore the growing importance of climate adaptation strategies for sustaining agricultural productivity in the region.

2-3- Sampling Methods

The target population consisted of all agricultural households engaged in crop production within the three selected districts of the Fergana Valley. According to official data from the State Committee on Statistics of Uzbekistan, this population comprises 12,450 registered farms (9,735 Dehkan farms and 2,715 cluster farms) that cultivate approximately 185,000 ha of irrigated land.

The sample size was calculated using the following formula for finite population proportion estimation:

$$n = (Z^2pq) / (e^2) \times [N/(N-1)] \tag{1}$$

where Z = 1.96 (95% confidence level), p = 0.5 (maximum variance assumption), q = 1-p = 0.5, e = 0.07 (7% margin of error), and N = 12,450 (total farm population). The calculated minimum sample size of 165 farms was increased to 175 farms (12% buffer) to account for potential nonresponse and data quality issues.

A screening process based on prespecified inclusion and exclusion criteria was used to construct the sampling frame. Eligible holdings were required to have adopted at least five CSA technologies or practices during the reference season, and to provide documented evidence of access to credit or public subsidies supporting CSA, such as loan agreements, subsidy contracts, or entries in official program registries. Farms were also required to maintain complete production and agro-ecological records for both the baseline and post-adoption periods and to report no changes in managerial control over the observation window. Relevant knowledge and capacity are required, given the study's focus on informed adoption under realistic institutional conditions. This included a minimum of two contacts with agricultural extension services within the preceding 12 months or the completion of a certified CSA or irrigation training course, combined with a score of at least 60% on a five-item CSA knowledge assessment administered during enrollment.

Additionally, the farms were verified to face no binding institutional constraints that would prevent the adoption of less common CSA technologies. Specific requirements included active membership in good standing within a Water Users Association (WUA), water allocation arrangements compatible with off-season cover cropping, absence of crop-mandate or procurement clauses prohibiting such practices, secure land-use rights or leases with at least three years remaining, and eligibility for district-level distributed solar pumping programs with no history of application denials.

Farms were excluded if they adopted fewer than five climate-smart agriculture practices, lacked verifiable access to financing, provided incomplete or inconsistent data, participated in concurrent programs that could confound the same outcomes, specialized in non-field crops (e.g., livestock-only or greenhouse operations), experienced severe exogenous shocks during the observation period (e.g., extreme weather events or pest outbreaks), or faced binding institutional constraints such as formal prohibitions on cover cropping, unresolved land tenure disputes, delinquent Water User Association (WUA) status resulting in water allocations below agronomic thresholds, or regulatory barriers to installing solar-powered irrigation pumps.

This study used random selection in sampling; 65 farms were allocated to Fergana (37.14% of the sample), 55 to Rishtan (31.43%), and 55 to Bag'dod (31.43%). The second stratum was the farm type, comprising 135 Dehkan farms (77.15%) and 40 cluster farms (22.85%). The third stratum reflected the primary crop orientation: 82 holdings focused on cotton (46.86%), 41 on wheat (23.44%), 33 on vegetables (18.85%), and 19 on mixed systems (10.85%). Systematic sampling with a random start was applied to the computer-randomized farm lists within each stratum. A brief verification process was conducted prior to contact, combining document reviews and preliminary screening interviews. To address anticipated non-response or late disqualification, pre-randomized replacement units were designated within the same stratum; cross-stratum substitution was not permitted, ensuring the preservation of the original allocation proportions. All units within a given stratum had equal inclusion probabilities; therefore, post-stratification weighting was not required.

2-4- Data Collection

Data were collected in three distinct phases between March and September 2024. The preparatory phase (March 2024) included the pre-testing of survey instruments with a sample of 15 farmers, calibration of field measurement equipment, and establishment of local partnerships with district agricultural departments. The primary data collection phase spanned April to September 2024 and comprised three sequential components.

Phase 1: Farmer surveys (April-June 2024): Structured interviews were conducted with farm household heads for an average of approximately 2 hours per interview. A total of 175 completed surveys were obtained from the selected sample of the farms, resulting in a response rate of 94.6% (Appendix I).

Phase 2: Field measurements (May-August 2024): In-situ assessments included soil erosion monitoring during the growing season, water quality testing during peak irrigation periods, and crop performance observations at key phenological stages.

Phase 3: Harvest data collection (August-September 2024): Crop yields were directly measured and validated, farm income was calculated and crosschecked, and final data quality assurance procedures were implemented.

Multiple data collection methods were employed to ensure comprehensive coverage of the research variables. Structured face-to-face interviews with farm household heads were conducted with trained members of the research team. The interviews captured information on CSA technology adoption patterns, farm characteristics, production practices, and socioeconomic indicators.

The survey data were complemented by field measurements obtained through direct observation and quantification of key environmental and productivity indicators. Soil erosion assessments were conducted during the growing season, when erosive processes are most active, using standardized visual scoring methods and quantitative measurement techniques.

To capture the full range of temporal variability in water characteristics, water quality samples were collected during the peak irrigation periods. Crop performance was monitored through scheduled field visits to track phenological development and to identify potential sources of yield variation across farms.

For harvest data collection, direct field measurements were triangulated with farmer-reported yield data to enhance the accuracy and reliability. Income calculations were based on detailed records of input and output prices, which were verified through cross-referencing prevailing market rates and agricultural input supplier documentation.

2-5- Variables and Measurements

2-5-1- Independent Variables: CSA Technologies

This study examined nine specific CSA technologies, selected based on their relevance to Central Asian agroecological conditions and the potential for adoption by smallholder farmers. Each technology was measured using a 4-point adoption scale to capture the variations in implementation intensity. Table 1 provides the definitions of these technologies.

Table 1. Definitions of climate-smart agricultural technologies; compiled by authors based on [89]

Technology	Definition
T1: Biopesticide use and crop and pest management	Use of biological agents (beneficial insects, microbial pesticides, and botanical extracts) instead of or in combination with synthetic pesticides for pest control
T2: Microdosing of fertilizer	Application of small, precise amounts of fertilizer (typically 2-6 g per plant) directly to individual plants or in micro-basins rather than broadcast application
T3: Application of organic manure	Systematic use of livestock manure, compost, or other organic materials to improve soil structure and fertility
T4: Application of compost	Decomposed organic matter (crop residues, household waste, and animal manure) prepared through controlled composting processes
T5: Improved flood-tolerant varieties	Cultivation of crop varieties specifically bred or selected for waterlogging and flooding tolerance
T6: Green energy-based irrigation (solar pumps)	Solar-powered pumping systems for irrigation water delivery, reducing dependence on grid electricity or diesel pumps
T7: Early maturing varieties	Cultivation of crop varieties with shortened growing seasons, allowing drought avoidance and multiple cropping potential
T8: Pit planting and improved planting methods	Concentrated planting techniques including zaï pits, raised beds, or precision planting, to improve water and nutrient use efficiency
T9: Cover crops/intercropping	Growing secondary crops between main crop seasons or intercropping systems to improve soil health and resource use efficiency

Measurement scales for CSA technologies follow a consistent ordinal structure adapted to each practice's specific nature. The scale for biopesticides and crop management practices ranges from never used (1) to used on more than 75%

of farm area (4). Micro-dosing of fertilizers is measured from never practiced (1) to applied to more than 75% of crops (4). Organic manure application is quantified from no organic inputs (1) to more than 15 tons per hectare annually (4). Similarly, compost application is scored from no compost use (1) to application exceeding 10 tons per hectare annually (4).

Adoption of improved crop varieties, including flood-tolerant and early maturing varieties, is assessed based on the proportion of cultivated area planted with such varieties, ranging from “only traditional varieties used” (1) to “more than 75% of area under improved varieties” (4). Solar-powered irrigation adoption was measured as the percentage of the total irrigation volume supplied by renewable energy sources. Improved planting methods are evaluated on a scale from “traditional broadcasting” (1) to “use of improved techniques on more than 75% of planting area” (4). Cover cropping and intercropping were measured according to the proportion of farm areas that employed these practices, with higher scores indicating greater implementation intensity.

2-5-2- Dependent Variables: Agricultural and Environmental Outcomes

This study analyzed five key dependent variables representing agricultural productivity and environmental performance outcomes. These variables capture the multidimensional impacts of farm-level CSA technology adoption, as shown in Table 2.

Table 2. Agricultural and environmental variables of outcome

Outcome Variable	Definition	Unit of measurement
Y1: Crop yields	Primary productivity indicator measured separately for major crops (cotton, wheat, and vegetables) based on actual harvest data and farmer records	kg ha^{-1} yr^{-1}
Y2: Income per unit area	Net farm income is calculated as gross revenue minus variable costs per hectare	USD ha^{-1} yr^{-1}
Y3: Resource use efficiency	Ratio of gross output value to total input costs, indicating the effectiveness of conversion of inputs to economic returns	Ratio
Y4: Soil erosion score	Visual assessment and erosion severity measurement-based scoring	1-5 Scale
Y5: Water quality index	Composite indicator based on salinity, pH, and nutrient levels in irrigation return flows and drainage water	1-10 Scale

Crop yield is the primary productivity measure and is calculated separately for major crops, including cotton, wheat, and vegetables, based on actual harvest data and verified farm records. This metric captures the direct production impact of adopting CSA technology across the dominant cropping systems in the study area.

Income per unit area, expressed as net farm income per hectare, was used as an indicator of economic performance. Net income is calculated as the total crop sales revenue minus variable costs, including seeds, fertilizers, pesticides, fuel, and labor. Standardization by hectare enables valid comparisons across farms of varying sizes and facilitates economic efficiency analysis.

Resource-use efficiency is measured as the ratio of gross output value to total input costs, providing an indicator of how farmers effectively convert agricultural inputs into economic returns. This efficiency metric reflects the potential of CSA technologies to optimize input-output relationships and improve farm-level profitability.

The ratio of gross output value to total input costs was used to calculate resource-use efficiency, providing an indicator of the effectiveness with which farmers convert agricultural inputs into economic returns. This measure enables an assessment of the optimization potential of CSA technologies to improve input-output relationships.

Soil erosion was assessed using a visual and measurement-based scoring system, with a score of 1 indicating no visible erosion, 2 indicating slight erosion, 3 indicating moderate erosion, 4 indicating severe erosion, and 5 indicating severe erosion with gully formation. This environmental indicator reflects soil conservation outcomes associated with CSA practices.

The water quality index (WQI) is a composite metric derived from multiple parameters, including salinity (measured as electrical conductivity), pH levels, and nutrient concentrations (nitrogen and phosphorus) in irrigation return flows and drainage water. The index ranged from 1 to 10, with higher values indicating improved water quality.

2-5-3- Control Variables

The analysis incorporated several control variables to account for factors that may influence the relationship between the adoption of CSA technologies and agricultural outcomes. Farm-level characteristics include farm size (measured in hectares), age and education level, years of farming experience, access to credit and extension services, and distance to markets. Environmental factors within the study area included soil type, initial fertility status, irrigation water quality, and microclimatic variations. These variables help isolate the effects of CSA adoption by controlling for farm and environmental heterogeneity, which can independently affect agricultural performance.

2-6- Data Analysis

The collected data were analyzed using descriptive and inferential statistical methods. Descriptive statistics, including means, standard deviations, and frequency distributions, were computed to characterize the patterns of CSA technology adoption and agricultural outcome variables. A correlation analysis was conducted to examine the bivariate relationships between CSA technologies and outcome indicators. Multiple regression analysis was used to estimate the individual effects of each CSA technology on agricultural and environmental outcomes, while controlling for potential confounding variables. A one-way analysis of variance was used to compare outcomes across different levels of technology adoption. ROI was calculated to evaluate the economic viability of each technology. All statistical analyses were performed using IBM SPSS Statistics (version 28.0), with statistical significance defined at $p < 0.05$.

3- Results

3-1- CSA Technology Adoption Patterns

The collected data were analyzed using descriptive and inferential statistical methods. Descriptive statistics including means, standard deviations, and frequency distributions were computed to characterize the patterns of CSA technology adoption and key agricultural outcome variables. Correlation analysis was performed to examine bivariate relationships between CSA and outcome indicators. Multiple regression models were employed to estimate the individual effects of each technology on agricultural and environmental outcomes, while controlling for potential confounding factors. A one-way analysis of variance was conducted to compare the outcomes across different adoption levels. ROI was calculated to assess the economic viability of each technology. All analyses were performed using IBM SPSS Statistics (version 28.0), with statistical significance set at $p < 0.05$. Analysis of CSA adoption among 175 farms in the Fergana Valley revealed significant variation in implementation levels across different technologies. As shown in Table 3, micro-dosing demonstrated the highest adoption rate with a mean score of 3.42, and 67% of farms implemented this technology at high levels. Organic manure application was the second most adopted practice, with a mean score of 3.18 and a high adoption rate of 58%. These findings indicate that farmers have readily implemented soil fertility management practices that align with traditional agricultural knowledge and offer tangible productivity benefits.

Table 3. CSA adoption levels among the farms under study

CSA Technology	Mean Score	Std. Dev.	Adoption Level	% Highly Adopted	% Never Adopted
Fertilizer micro-dosing	3.42	0.78	High	67%	8%
Application of organic manure	3.18	0.85	High	58%	12%
Early maturing varieties	2.95	0.92	Moderate	45%	18%
Improved planting methods	2.87	0.89	Moderate	42%	21%
Biopesticides/pest management	2.73	0.96	Moderate	38%	25%
Compost application	2.65	1.02	Moderate	35%	28%
Solar-powered irrigation	2.31	1.15	Low	25%	42%
Flood-tolerant varieties	2.08	1.08	Low	18%	48%
Cover crops/intercropping	1.89	0.95	Low	12%	55%

Moderately adopted CSA technologies included early maturing varieties (mean score: 2.95), improved planting methods (2.87), biopesticides (2.73), and compost application (2.65). These practices exhibit high implementation rates ranging between 35% and 45%, indicating growing farmer interest but also indicating the presence of barriers to broader adoption. The lowest adoption levels were observed for cover crops and intercropping (1.89), flood-tolerant varieties (2.08), and solar-powered irrigation systems (2.31), with more than 40% of the farmers reporting no use of these technologies.

3-2- Agricultural and Environmental Outcomes

Descriptive analyses of the agricultural and environmental outcome variables revealed considerable variation across farms (Table 4). Cotton yields averaged 3,245 kg ha^{-1} yr^{-1} (standard deviation = 567), with values ranging from 2,100 to 4,800 kg ha^{-1} yr^{-1}. Wheat yields exhibited higher average productivity, reaching 4,180 kg ha^{-1} yr^{-1}, while vegetable yields displayed the greatest variability, with a mean of 18,750 kg ha^{-1} yr^{-1} and a range of 12,500 to 28,000 kg ha^{-1} yr^{-1}.

Table 4. Descriptive statistics of agricultural and environmental outcome variables

Impact Variable	Mean	Std. Dev.	Min	Max	Unit
Cotton yield	3,245	567	2,100	4,800	kg ha^{-1} yr^{-1}
Wheat yield	4,180	623	2,900	5,650	kg ha^{-1} yr^{-1}
Vegetable yield	18,750	3,240	12,500	28,000	kg ha^{-1} yr^{-1}
Income per hectare	2,847	891	1,250	5,200	USD ha^{-1} yr^{-1}
Soil erosion score	2.8	1.2	1	5	Scale 1-5
The water quality index	6.7	1.8	3.2	9.8	Scale 1-10
Resource efficiency	2.34	0.67	1.12	4.15	Ratio

The farm income per hectare averaged USD 2,847, with considerable variation (standard deviation = 891), indicating significant economic disparities across farms. The environmental indicators revealed moderate levels of soil erosion (mean score: 2.8 on a 5-point scale) and an average water quality index of 6.7 (on a 10-point scale). The resource use efficiency ratio averaged 2.34, meaning that farms generated approximately USD 2.34 in output value for each dollar invested in inputs.

3-3- Relationships Between the CSA Technologies and Outcomes

The correlation analysis revealed a significant positive association between CSA technology adoption and agricultural outcomes (Table 5). Fertilizer micro-dosing exhibited the strongest correlations with all yield variables, with coefficients of 0.45, 0.38, and 0.52 for cotton, wheat, and 0.52 for vegetable yield, respectively (all $p < 0.001$). This practice also demonstrated a strong positive correlation with farm income per hectare ($r = 0.48$, $p < 0.001$), and a moderate negative correlation with soil erosion ($r = -0.35$, $p < 0.01$).

Table 5. Correlation matrix between CSA technologies and outcome variables

	Cotton Yield	Wheat Yield	Vegetable Yield	Income/ha	Soil Erosion	Water Quality	Resource Efficiency
Fertilizer micro-dosing	0.45***	0.38***	0.52***	0.48***	-0.35**	0.29**	0.41***
Organic manure	0.41***	0.43***	0.48***	0.44***	-0.42***	0.38***	0.39***
Early maturing varieties	0.38***	0.35**	0.31**	0.36***	-0.21*	0.18	0.33**
Improved planting	0.33**	0.29**	0.35**	0.32**	-0.28**	0.25*	0.31**
Biopesticides	0.28**	0.24*	0.41***	0.34**	-0.18	0.33**	0.29**
Compost application	0.35**	0.40***	0.43***	0.38***	-0.39***	0.35**	0.36**
Solar irrigation	0.22*	0.19	0.28**	0.31**	-0.15	0.41***	0.27*
Flood-tolerant varieties	0.19	0.34**	0.26*	0.25*	-0.24*	0.22*	0.21
Cover crops	0.25*	0.31**	0.33**	0.29**	-0.36**	0.28**	0.26*

*p < 0.05, **p < 0.01, ***p < 0.001

Organic manure application showed consistently strong associations with all outcome variables, particularly exhibiting a significant negative correlation with soil erosion ($r = -0.42$, $p < 0.001$) and a positive correlation with water quality ($r = 0.38$, $p < 0.001$). Solar-powered irrigation demonstrated the strongest association with improved water quality ($r = 0.41$, $p < 0.001$), whereas cover crops and intercropping were significantly correlated with reduced soil erosion ($r = -0.36$, $p < 0.01$). All CSA technologies exhibited positive correlations with RUE, suggesting their potential to enhance IOP in agricultural systems.

3-4- Impact of CSA Technologies on Cotton Yield

Multiple regression analysis examining the impact of CSA technologies on cotton yields revealed statistically significant positive effects for seven of the nine technologies (Table 6). The model accounted for 57.3% of the variance in cotton yield ($R^2 = 0.573$, $F(9,175) = 26.1$, $p < 0.001$), indicating a strong explanatory power.

Table 6. **Multiple Regression Analysis-Cotton Yield (kg ha^{-1} yr^{-1})**

CSA Technology	Coefficient	Std. Error	t-value	p-value	95% CI
Constant	1,845.60	156.3	11.81	<0.001	1,538.2 - 2,153.0
Fertilizer micro-dosing	245.8	42.7	5.76	<0.001***	161.7 - 329.9
Organic manure	189.3	38.9	4.87	<0.001***	112.8 - 265.8
Early maturing varieties	156.4	35.2	4.44	<0.001***	86.9 - 225.9
Improved planting	123.7	41.1	3.01	0.003**	42.8 - 204.6
Biopesticides	98.5	33.8	2.91	0.004**	31.9 - 165.1
Compost	87.2	29.6	2.95	0.004**	28.8 - 145.6
Solar irrigation	76.3	31.4	2.43	0.016*	14.3 - 138.3
Flood-tolerant varieties	45.9	28.7	1.6	0.112	-113.8
Cover crops	67.8	32.1	2.11	0.036*	4.5 - 131.1

Notes: Model statistics: $R^2 = 0.573$, Adjusted $R^2 = 0.551$, $F(9,175) = 26.1$, $p < 0.001$

Fertilizer micro-dosing has the largest positive effect on cotton yields, increasing production by 245.8 kg ha^{-1} yr^{-1} ($p < 0.001$), followed by organic manure application, which contributes an additional 189.3 kg ha^{-1} yr^{-1} ($p < 0.001$). Early maturing varieties are associated with a yield increase of 156.4 kg ha^{-1} yr^{-1} ($p < 0.001$), whereas improved planting methods result in an increase of 123.7 kg ha^{-1} yr^{-1} ($p < 0.01$). All CSA technologies, except for flood-tolerant varieties, exhibited statistically significant positive effects on cotton yield.

3-5- Analysis of the Economic Impact

The economic impact analysis (Table 7) revealed that the adoption of CSA technologies significantly affects farm income per hectare. The regression model explained 61.8% of the variance in income ($R^2 = 0.618$, $F(9,175) = 31.4$, $p < 0.001$), indicating strong predictive power for economic outcomes.

Table 7. **Multiple regression analysis-income per hectare (USD ha^{-1} yr^{-1})**

CSA Technology	Coefficient	Std. Error	t-value	p-value	95% CI
Constant	1,234.50	98.7	12.51	<0.001	1,039.6 - 1,429.4
Fertilizer micro-dosing	387.6	67.2	5.77	<0.001***	255.0 - 520.2
Organic manure	298.4	61.3	4.87	<0.001***	177.4 - 419.4
Early maturing varieties	245.8	55.4	4.44	<0.001***	136.5 - 355.1
Improved planting	194.7	64.7	3.01	0.003**	67.2 - 322.2
Biopesticides	155.1	53.2	2.91	0.004**	50.2 - 260.0
Compost	137.3	46.6	2.95	0.004**	45.4 - 229.2
Solar irrigation	234.6	59.8	3.92	<0.001***	116.7 - 352.5
Flood-tolerant varieties	123.4	52.1	2.37	0.019*	20.6 - 226.2
Cover crops	156.8	55.9	2.8	0.006**	46.4 - 267.2

Model Statistics: $R^2 = 0.618$, Adjusted $R^2 = 0.598$, $F(9,175) = 31.4$, $p < 0.001$

Fertilizer micro-dosing yields the highest economic return, increasing farm income by 387.6 USD ha^{-1} yr^{-1} ($p < 0.001$), followed by organic manure application, which contributes an increase of 298.4 USD ha^{-1} yr^{-1} ($p < 0.001$). Early maturing varieties are associated with an income gain of 245.8 USD ha^{-1} yr^{-1} ($p < 0.001$), while solar-powered irrigation adds 234.6 USD ha^{-1} yr^{-1} ($p < 0.001$). All CSA technologies exhibited statistically significant positive effects on farm income, underscoring their economic viability for farmers in the study region.

3-6- Environmental Impact Assessment

Multiple regression analysis of the soil erosion scores revealed significant environmental benefits associated with the adoption of CSA technologies (Table 8). The model explained 48.7% of the variance in soil erosion outcomes ($R^2 = 0.487$, $F(9,175) = 18.5$, $p < 0.001$), with negative regression coefficients indicating reduced soil erosion.

Table 8. Multiple Regression Analysis-Soil Erosion Score (1-5 scale, higher = worse)

CSA Technology	Coefficient	Std. Error	t-value	p-value	95% CI
Constant	4.23	0.18	23.5	<0.001	3.87 - 4.59
Fertilizer micro-dosing	-0.28	0.09	-3.11	0.002**	-0.36
Organic manure	-0.34	0.08	-4.25	<0.001***	-0.32
Early maturing varieties	-0.15	0.07	-2.14	0.034*	-0.28
Improved planting	-0.19	0.08	-2.38	0.018*	-0.32
Biopesticides	-0.12	0.07	-1.71	0.089	-0.28
Compost	-0.31	0.06	-5.17	<0.001***	-0.24
Solar irrigation	-0.08	0.08	-1	0.319	-0.32
Flood-tolerant varieties	-0.14	0.07	-2	0.047*	-0.28
Cover crops	-0.26	0.07	-3.71	<0.001***	-0.28

Model Statistics: $R^2 = 0.487$, Adjusted $R^2 = 0.461$, $F(9,175) = 18.5$, $p < 0.001$

Compost application was associated with the largest reduction in soil erosion scores, decreasing them by 0.31 points ($p < 0.001$), followed by organic manure application, which reduced scores by 0.34 points ($p < 0.001$). Cover crops significantly reduced erosion by 0.26 points ($p < 0.001$), and fertilizer microdosing resulted in a 0.28-point decline ($p < 0.01$). Collectively, these results indicate that organic-matter-based CSA technologies are strongly linked to improved soil conservation outcomes.

3-7- Analysis of the Adoption Level Impact

An ANOVA examining agricultural outcomes across different levels of climate-smart agriculture technology adoption revealed significant differences in farm performance (Table 9). Farms were classified into three groups based on adoption intensity: low (1-2 technologies), medium (3-5 technologies), and high (more than 6 technologies).

Table 9. Economic impact analysis by CSA adoption level

Adoption Level	N	Mean Income (USD/ha)	Std. Dev.	Mean yield (kg/ha)	Resource Efficiency
Low Adoption (1-2 technologies)	47	2,145	578	2,890	1.95
Medium Adoption (3-5 technologies)	89	2,847	634	3,420	2.34
High adoption (6+ technologies)	49	3,678	789	4,125	2.89
ANOVA F-statistic		$F(2,182) = 42.7$***		$F(2,182) = 38.4$***	$F(2,182) = 31.2$***

Analysis of variance revealed significant differences in agricultural performance across CSA technology adoption levels (Table 9). Farms were classified into three groups based on adoption intensity: low (1-2 technologies), medium (3-5 technologies), and high (more than 6 technologies). High adopters achieve a 71% higher income per hectare (3,678 USD ha^{-1}) compared to low adopters (2,145 USD ha^{-1}), reflecting a substantial economic advantage. Crop yields increased by 43% from low to high adoption levels, rising from 2,890 kg ha^{-1} to 4,125 kg ha^{-1}. Resource use efficiency improved by 48%, increasing from 1.95 2.89. All intergroup differences were statistically significant ($p < 0.001$), indicating clear benefits associated with the implementation of broader CSA technology.

Figure 3 illustrates the positive relationship between the number of CSA technologies adopted and key farm performance indicators. The visualization shows a progressive improvement in economic returns and resource efficiency as adoption intensity increases. Income per hectare rose substantially (from 2,145 to 3,678 USD ha^{-1}), representing a 71% gain for high adopters. Similarly, RUE followed a consistent upward trend, increasing from 1.95 to 2.89, implying that farms adopting multiple CSA practices achieved significantly better IOP. This graphical representation reinforces the ANOVA results and underscores the cumulative benefits of comprehensive technology adoption, indicating that integrated implementation yields greater improvements than isolated practices.

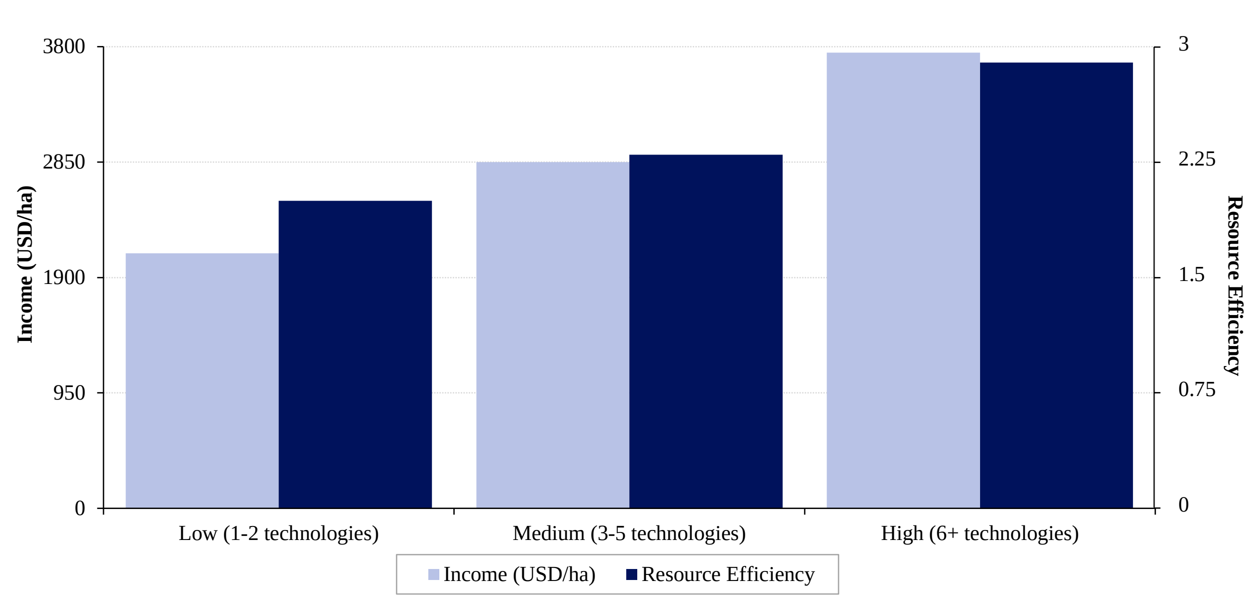

Figure 3. **Farm performance according to the level of CSA adoption**

3-8- Analysis of the Return on Investment

An assessment of the economic viability of individual CSA technologies reveals considerable variation in the ROI and payback periods, as detailed in Table 10. Fertilizer micro-dosing exhibits exceptional financial performance, yielding a 456% return on investment and a payback period of just 0.22 years, making it the most economically attractive technology for farmers.

Table 10. **Technology-specific return on investment analysis**

CSA Technology	Implementation cost (USD/ha)	Increase in yield (%)	Increase in income (USD/ha)	ROI (%)	Payback period (years)
Fertilizer micro-dosing	85	15.20%	388	456%	0.22
Organic manure	120	12.80%	298	248%	0.4
Early maturing varieties	65	11.50%	246	378%	0.26
Improved planting	45	8.70%	195	433%	0.23
Biopesticides	95	7.20%	155	163%	0.61
Compost application	75	6.80%	137	183%	0.55
Solar irrigation	850	5.50%	235	28%	3.62
Flood-tolerant varieties	180	4.30%	123	68%	1.46
Cover crops	110	5.80%	157	143%	0.7

Improved planting methods and early maturing varieties also exhibited strong economic performance, yielding returns on investment of 433% and 378%, respectively, with a payback period of less than one year. Organic manure application provided moderate but reliable returns, with an ROI of 248% and relatively low implementation costs. In contrast, while offering notable environmental benefits, solar-powered irrigation requires the highest initial investment (850 USD ha^{-1}) and has the longest payback period (3.62 years), which may limit its adoption among resource-constrained farmers. These results offer valuable insights for farmers and policymakers in prioritizing CSA technologies based on their economic feasibility and return potential.

Economic calculations over a six-season time horizon (T = 6) were performed to assess the economic viability of the CSA technologies, with one main cropping season per year (Table 11). The base parameters are presented in Table 10. The model incorporates three key sources of uncertainty. The first key source is risk of adverse growing seasons: with probability p, the revenue effect is reduced to a fraction β of the normal level (e.g., due to drought, flooding, or pest outbreaks). The second key source of uncertainty is known as learning-by-doing: technology effectiveness gradually increases by a factor of λ per season as farmers gain experience. Finally, there are recurring operational costs: some technologies require seasonal expenditures, approximated as a fraction φ of the initial investment cost (higher for inputs such as seeds, bioinputs, and organic amendments, and lower for capital-intensive investments).

Although point estimates of ROI and payback periods offer valuable insights into the economic attractiveness of individual CSA technologies, they may not fully capture the dynamic and uncertain nature of real-world farming environments. To address this, a discounted cash flow (DCF) model was developed to simulate the economic performance of selected CSA practices over a six-season horizon, incorporating critical uncertainties such as climatic shocks, learning effects, and recurring operational costs.

Table 11 summarizes the results of this simulation, reporting net present value (NPV), ROI, and payback periods under both baseline and adverse yield scenarios. These results offer a more nuanced understanding of long-term technology viability, especially for interventions with delayed returns or high upfront costs. Technologies are assessed not only on their average performance but also on their resilience to poor growing seasons and operational scalability.

Table 11. Return on investment in CSA technologies over six seasons, accounting for the risk of poor-yield seasons (per hectare)

CSA	Initial cost (USD/ha)	Recurrent cost per season (USD/ha)	Increase in income during the normal season (USD/ha)	NPV over 6 seasons (USD/ha)	ROI over 6 seasons (%)	Expected payback (seasons)	NPV: 2 bad seasons (USD/ha)	ROI: 2 bad seasons (%)	Payback: 2 bad seasons
Fertilizer micro-dosing	85	42.50	388	1,320.12	1553.1	1	1,253.49	1474.7	1
Early maturing varieties	65	52.00	246	716.76	1102.7	1	674.51	1037.7	1
Improved planting	45	9.00	195	715.01	1588.9	1	681.52	1514.5	1
Organic manure	120	120.00	298	578.72	482.3	1	527.54	439.6	1
Cover crops	110	77.00	157	198.11	180.1	2	171.15	155.6	3
Compost application	75	75.00	137	159.85	213.1	2	136.32	181.8	3
Biopesticides	95	95.00	155	126.52	133.2	3	99.90	105.2	3
Solar irrigation	850	42.50	235	-71.95	-8.5	>6	-112.31	-13.2	>6
Flood-tolerant varieties	180	108.00	123	-146.25	-81.3	>6	-167.38	-93.0	>6

Notes: Global parameters – bad-season probability p = 0.25; bad-season factor β = 0.60; learning rate λ = 0.02 per season; discount rate r = 0.10 per season; horizon T = 6 seasons. The recurrent-cost fractions φ are technology-specific. The NPV is reported in USD/ha, and the ROI is calculated as NPV/C_0 × 100%. Payback reports the first season when the discounted cumulative net benefits equal or exceed C_0 . '2 adverse seasons" scenario assumes exactly two adverse seasons (2 and 4).

Improved planting methods, fertilizer micro-dosing, and early maturing varieties are recouped within one to two seasons, and a high ROI is maintained even under adverse growth conditions (Table 11). Technologies with high recurring input costs (organic amendments, compost, and bioinputs) remain economically viable. Solar-powered irrigation is profitable primarily over longer time horizons and under low-cost financing conditions; however, its payback period remains extended. Risk mitigation related to poor yield seasons and the positive effects of learning-by-doing significantly improve profitability trajectories. Therefore, to ensure short-term liquidity, an optimal strategy involves combining quick-return CSA technologies with gradual adoption of more complex and capital-intensive practices.

4- Discussion

Numerous CSA initiatives have been implemented across the Fergana region in recent years, reflecting increasing national commitment and donor interest in sustainable intensification within irrigated agroecosystems. These efforts span a wide range of interventions, from irrigation modernization and greenhouse innovation to institutional reforms in water governance and digital agricultural services. To contextualize the present study within this evolving policy and project landscape, Table 12 synthesizes the key CSA initiatives in Uzbekistan's Fergana region, detailing their implementation periods, geographic coverage, technological components, outcome indicators, and performance metrics. The projects listed reflect various entry points into CSA programming, ranging from farm-level technologies (e.g., drip irrigation, pest management) to system-level enablers (e.g., water user associations and smart extension models).

Table 12. Climate-smart agriculture technologies adopted in the Fergana region: components, indicators, and outcome metrics

Project	Period	Geographic distribution	CSA	Reported outcomes and indicators	Improvements in performance (baseline–endline)	Data Source(s)
Smart Farming for the Future Generation	2020–2025	Andijan, Namangan, and Fergana, including Novkent and Yuksalish villages	Greenhouse CSA packages: drip irrigation and fertigation; climate management; IPM/pest traps; digital skills and market access; nutrient and water monitoring (pH/EC meters)	20 household greenhouses upgraded; 60 farms benefited by 2025, around 65% women beneficiaries; improved input-use efficiency (water, fertilizers); safer agrochemical handling (gender-responsive training)	20 upgraded greenhouses (from 0); more 60 direct beneficiaries (67% women); improved water/fertilizer efficiency; enhanced safety in agrochemical use	[9, 89-92]
Digital Villages Initiative in the Fergana Region	2023-ongoing	Novkent, Yuksalish	Smart greenhouses; digital tools and services; market access; training and twinning; water smart greenhouse practices	Qualitative evidence of adoption, case stories, and integration with the Smart Farming project	Adoption of smart greenhouse technology and digital services	[89, 91]
World Bank – Ferghana Valley Water Resources Management Project Phase II	2017–2026 (extended)	Fergana Region	Irrigation and drainage modernization (143 km of canals, 578 distribution structures, 494 wells, and 13 pumping stations); EU TA on WUAs, volumetric O&M payments, and solar pumps; digitalization and water accounting	Irrigation service quality improved on 48,410 ha (47% of area); 33,689 farmers gained benefits by August 2024; scheme efficiency targeted from 60% to 80%; energy use reduced via pump modernization	Irrigation efficiency increased from around 60% to 80%; 48,410 ha served (up from 0); 33,689 beneficiaries reached (up from 0)	[93, 94]

Notes: CSA, climate-smart agriculture; WUA, Water Users Association; WUE, water use efficiency; ICWC, Interstate Commission for Water Coordination; KRASS, National Association of Farmers' Water User Associations of Uzbekistan; IWMI, International Water Management Institute; ICARDA, International Center for Agricultural Research in the Dry Areas; WLE, CGIAR Research Program on Water, Land and Ecosystems; DVI, Digital Village Initiative.

Although state-mandated quotas for cotton and wheat have been formally abolished in Uzbekistan since 2020, the agricultural sector has been shaped by enduring state involvement in land use decisions, irrigation management, and procurement practices. These legacy structures rooted in decades of centralized planning continue to influence what crops are grown, how inputs are allocated, and how market access is structured. In the Fergana Region, over 70% of arable land is still informally aligned with state-preferred crops, and the irrigation infrastructure is managed centrally. Such institutional realities significantly affect the feasibility and scalability of CSA. Therefore, the discussion of our results is framed within this hybrid policy environment, in which formal liberalization and operational centralization coexist. This allows for a more grounded interpretation of the findings, particularly regarding the variation in adoption intensity and observed barriers to technology uptake.

While the aforementioned initiatives demonstrate progress in promoting CSA adoption, most report only descriptive or intermediate outcomes, with limited rigorous assessments of economic returns, environmental co-benefits, or long-term scalability. Few studies have provided farm-level quantitative data suitable for impact evaluation. This underscores a critical gap that the current study addresses: by combining robust empirical analysis with comprehensive household-level data, the authors move beyond project-specific reporting to deliver generalizable evidence on the productivity, profitability, and sustainability impacts of CSA in ICA in Central Asia.

Survey responses and qualitative interviews indicate that adoption decisions are shaped not only by cost-benefit calculations but also by farmers' perceived compatibility of technologies with established production systems and social norms. For example, cover crops, despite their well-documented agronomic benefits, are often perceived as misaligned with dominant cotton-wheat rotations. Farmers voiced concerns regarding competition for water and nutrients, disruption of irrigation cycles, and uncertainty regarding operational feasibility under local regulatory and climatic conditions. These perceptions suggest that adoption is constrained by both the lack of agronomic familiarity and the absence of a cultural precedent, which limits the cognitive legitimacy of such practices in local farming logic.

This study provides empirical evidence of the significant positive impacts of CSA technology adoption on agricultural productivity and environmental outcomes in Uzbekistan's intensive cotton-wheat farming systems. Substantial variation in adoption patterns was observed, with fertilizer micro-dosing and organic manure application being the most widely implemented practices, whereas cover crops, intercropping, and flood-tolerant varieties remained underutilized. These patterns align with the global trends reported by [34, 41, 57], who found that farmers tend to prioritize technologies delivering immediate and tangible benefits over those requiring long-term investments or major changes to established farming practices.

The quantitative analysis revealed that CSA technology adoption is associated with substantial productivity gains. Regression models explain 57.3% and 61.8% of the variation in cotton yield and farm income, respectively, indicating a strong explanatory power. Fertilizer micro-dosing has emerged as the most impactful practice, increasing cotton yields by 245.8 kg ha^{-1} yr^{-1} and farm income by 387.6 USD ha^{-1} yr^{-1}. These results are consistent with the findings from Kapoor and Pal [88] in semi-arid Karnataka, who documented significant income improvements following CSA adoption, although the magnitude of the impact in Uzbekistan's irrigated systems appears greater than in rainfed environments. The strong performance of soil fertility management practices, particularly fertilizer micro-dosing and organic manure application, supports earlier evidence in Ethiopia [95] where soil health-enhancing technologies were identified as key components of smallholder resilience strategies.

The results indicated substantial environmental benefits associated with the adoption of CSA technology, with key practices reducing soil erosion scores by 0.28 to 0.34 points. These findings provide empirical support for long-standing theoretical assertions regarding CSA's environmental advantages of CSA. Compost application and organic manure use exhibit the strongest soil conservation effects, reducing erosion by 0.31 and 0.34 points, respectively, which is consistent with the findings of Zuma-Netshiukhwi et al. [20], who emphasized the positive impacts of organic matter-based practices on soil health. A positive association was observed between CSA adoption and water quality improvement, with correlation coefficients ranging from 0.22 0.41. This aligns with European studies [49] that documented similar environmental co-benefits from climate-smart agricultural practices.

Analysis of adoption intensity reveals a clear performance gradient: farms classified as high adopters (6+ technologies) achieve 71% higher income per hectare and 43% greater crop yields than those classified as low adopters (1-2 technologies). This pattern underscores the cumulative benefits of integrating multiple CSA technologies, supporting the holistic approach advocated by Saran et al. [31], and implying synergistic interactions among practices. Furthermore, resource use efficiency increases by 48% among high adopters (from 1.95 to 2.89), demonstrating the potential of CSA to reconcile agricultural intensification with sustainability goals, thereby addressing the trade-off highlighted in Pretty et al. [66].

However, the uptake of advanced technologies is limited, with only 25% of farmers achieving high adoption levels for solar-powered irrigation and 12% to cover crops. This reflects the persistent barriers that have been widely documented in literature. The findings of this study are consistent with those of Ishtiaque et al. [96] and Pedersen et al. [97], who identified financial constraints, technical complexity, and institutional barriers as key impediments to the widespread adoption of CSA technologies. The high implementation cost of solar-powered irrigation (850 USD ha^{-1}) and its extended payback period of 3.62 years illustrate the significant capital limitations faced by smallholder farmers in developing countries.

Unlike the prior researches mostly focused on individual factors and aspects [19, 57] of sustainable agriculture and adoption technologies in Asia [97-102], in rainfall-dependent systems in Africa [104-108], the present study provides complex contributions based on primary data, multi-season estimations, and strict analysis of economic efficiency. This study provides over 6 seasons ROI and payback periods for CSA technologies, and develops targeted policy instruments for irrigated agriculture.

4-1- Theoretical Contribution

This study advances the theoretical foundation for agricultural development by refining and expanding existing paradigms through empirically grounded findings.

First, the results confirm that CSA adoption exerts a synergistic effect on enhancing productivity, agricultural resilience, and environmental sustainability. Quantitative verification of the positive impact of CSA practices on yield, income, resource-use efficiency, soil conservation, and water quality provides a robust methodological basis for further advancement of scientific knowledge in the field of CSA.

Second, the study clarifies the behavioral strategies of Uzbek farmers within the context of a distinct institutional environment, characterized by limited access to information, advisory services, and financial resources, as well as substantial state influence over decision-making in agriculture. These factors shape unique local patterns of technology adoption, determining both the pace and sequence of implementing climate-smart practices in irrigated systems.

Third, within the framework of agricultural intensification theory, this research specifies the relationship between the intensity of CSA adoption and agrarian performance. It demonstrates that adopting six or more CSA practices is associated with nonlinear gains in productivity and resource efficiency with significant implications for modeling marginal technology efficiency and optimizing agricultural policy.

Finally, this study presents an evaluation of CSA effectiveness in irrigated agroecosystems of Central Asia, a region with a unique institutional and environmental context conducive to the development of smart agriculture technologies. Thus, it extends the universality of CSA theoretical constructs and demonstrates their applicability across diverse agroecological and socioeconomic settings.

4-2- Practical Implications

These findings carry significant implications for policymakers, agricultural extension systems, and development practitioners operating within the agroecological landscapes of Asia. The exceptionally high ROI demonstrated by fertilizer micro-dosing (456% ROI, 0.22-year payback) and improved planting methods (433% ROI, 0.23-year payback) suggest that these technologies should be prioritized in extension programming and farmer training initiatives. Their short payback periods make them particularly well suited to resource-constrained holder farmers who depend on rapid financial returns to sustain adoption and reinvestment.

This study offers evidence-based guidance for government agencies and development organizations for the strategic allocation of resources in agricultural development programs. The substantial income gains associated with comprehensive CSA adoption (71% higher income for high adopters) highlight the potential of these technologies to reduce rural poverty and achieve food security goals. However, the high upfront costs of certain technologies, such as solar-powered irrigation (850 USD ha^{-1}), underscore the need for targeted financial support mechanisms. These may include subsidized credit schemes, grant programs, or innovative financing models such as pay-as-you-go solar systems, which can lower entry barriers and improve small-scale producers’ accessibility.

Given the cumulative performance benefits demonstrated by high adopters, extension service providers should prioritize the promotion of integrated technology packages over isolated practices. The strong effectiveness of organic-matter-based technologies (compost and manure application) assumes opportunities to align CSA initiatives with livestock development and waste management programs, enabling more holistic and synergistic rural development strategies.

For farmers, the findings provide a clear economic rationale for investing in CSA technologies, particularly in soil fertility management practices that deliver both immediate productivity gains and long-term environmental benefits. The documented improvements in soil conservation and water quality indicate that CSA adoption can serve as a practical approach for sustaining farm productivity over time while meeting increasingly stringent environmental regulations.

This study also reveals important implications for agribusiness and input supply chains, highlighting opportunities for precision application equipment, organic fertilizer production, and climate-resilient seed varieties. The high adoption rates observed for certain technologies imply that existing demand can support expanded commercial availability, greater competition, and reduced input costs through economies of scale.

4-3- Limitations and Recommendations for Future Studies

This study is subject to several methodological, measurement, and institutional limitations that should be considered when interpreting results and designing subsequent empirical or applied research.

First, existing systems for agricultural statistics and sectoral information support largely inherit practices from the centralized planned economy, increasing the risk of systematic biases in output, labor productivity, and production cost estimates. Incomplete and inconsistent primary records, data updating delays, heterogeneous definitions and methodologies, and the limited verifiability of field-level indicators reduce the accuracy of impact assessments and complicate cross-regional comparisons. The lack of reliable market information further constrains farmers' ability to adapt production and marketing strategies to volatile market conditions. These shortcomings also hinder the development and validation of evidence-based policy interventions tailored to actual sectoral impact.

Second, the study design limited the rigorous identification of causal relationships between the adoption of CSA practices and observed agricultural, economic, and environmental outcomes. Unobserved farm-level characteristics (such as management quality, entrepreneurial skills, or access to resources) may be correlated with the adoption of CSA technologies and performance outcomes. Future research should employ longitudinal panel data with intra-seasonal detail, quasi-experimental designs (e.g., natural experiments and phased program rollouts), and randomized controlled field trials to mitigate such biases where feasible.

Third, the sample is representative of conditions in the Fergana Valley, which is characterized by high irrigation coverage, specific water distribution regimes, and dominance of cotton-wheat crop rotations. Consequently, extrapolation of the findings to rainfed areas, different farming systems, or distinct socioeconomic contexts requires validation using comparable datasets from other regions of Uzbekistan and Central Asia.

Fourth, the environmental components relied primarily on erosion vulnerability indicators and localized water quality markers. Long-term watershed-scale monitoring, flow-weighted sampling, comprehensive nutrient balances, and systematic greenhouse gas (GHG) accounting are not available. These factors restrict the ability of irrigated systems to detect potential unintended consequences (nitrogen or phosphorus leaching, secondary salinization, or soil structural degradation) and delayed effects arising from large-scale technology adoption.

Fifth, economic viability estimates for certain practices, particularly fertilizer microdosing, were derived mainly from medium- and large-scale farms. When applied to smaller operations or different organizational configurations, factors such as input logistics, dosage calibration precision, application quality control, labor motivation, and access to specialized equipment and services may change significantly. These variables can either enhance or diminish returns, underscoring the need for targeted studies on technological scalability and sustainability across farm typologies.

Sixth, an in-depth analysis of adoption barriers for less widely used technologies (cover crops and solar-powered irrigation) was not feasible because the proportion of farms implementing these practices within the sample was too low to achieve sufficient statistical power for multivariate modeling or subgroup analyses.

Recognizing that Uzbekistan's agricultural sector still operates under considerable state influence, especially in terms of irrigation access, land use regulation, and pricing, policy reforms should be planned and designed for gradual implementation. Recommendations such as diversifying crop rotation and expanding private market access should be considered medium- to long-term goals that are compatible with the current hybrid system of partial liberalization. While our analysis controls for observable farmer characteristics, we acknowledge the potential for unobserved heterogeneity in managerial ability or motivation, which may influence both CSA adoption and outcomes. Future studies using panel data or experimental designs would be well positioned to disentangle these effects.

Although our findings point to the environmental co-benefits of CSA adoption, we recognize that potential negative externalities, such as nutrient leaching, were not directly measured. Future studies employing biophysical monitoring or simulation models would help assess these aspects more rigorously.

5- Conclusion

This study provides compelling empirical evidence that the adoption of CSA technologies significantly enhances agricultural productivity and environmental sustainability in Uzbekistan's irrigated systems. Based on a comprehensive analysis of 175 farms across Fergana Valley, CSA technologies deliver substantial economic returns and measurable environmental co-benefits. Fertilizer micro-dosing and organic manure application were the most successful practices, achieving high adoption rates of 67% and 58%, respectively, while generating exceptional financial performance. Fertilizer micro-dosing exhibits the strongest impact, increasing cotton yields by 245.8 kg ha^{-1} yr^{-1} and farm income by 387.6 USD ha^{-1} yr^{-1}, with a return on investment of 456% and a payback period of just 0.22 years. These findings establish soil fertility management as a cornerstone for effective CSA implementation in the region. This study further demonstrates the cumulative benefits of adopting comprehensive technology. Farms implementing six or more CSA technologies achieve 71% higher income per hectare, 43% greater crop yields, and 48% improved resource-use efficiency compared with low adopters. This indicates that CSA outcomes are maximized through integrated technology packages rather than through the isolated adoption of individual practices. The environmental benefits were also significant; compost application, organic manure use, and cover cropping reduced soil erosion scores by 0.31, 0.34, and 0.26 points, respectively. These results confirm that the climate-smart agriculture framework can achieve productivity enhancement and environmental conservation, thus challenging the notion of an inherent trade-off between intensification and sustainability. However, adoption of capital-intensive technologies remains limited. The low uptake of cover crops and intercropping (only 12% of farms achieved high adoption) and the substantial implementation cost of solar-powered irrigation (850 USD ha^{-1}) highlight the financial constraints faced by resource-limited farmers.

These findings underscore the need for differentiated and targeted CSA promotion strategies for policymakers. High-return, low-cost practices such as fertilizer micro-dosing and improved planting methods should be prioritized for rapid scaling through extension services and farmer training programs. In contrast, capital-intensive technologies, such as subsidized credit, grants, or pay-as-you-go financing, require financial mechanisms to overcome initial investment barriers. The results provide a strong economic rationale for public investment in CSA extension systems and demonstrate the potential of these technologies to meaningfully contribute to food security and environmental sustainability goals. Overall, this study establishes climate-smart agriculture as a viable and economically attractive pathway for sustainable development of irrigated farming systems in Central Asia. Findings across the productivity, economic, and environmental dimensions support increased CSA investment and policy backing, offering a synergistic strategy to enhance rural livelihoods while addressing pressing environmental challenges.

6- Declarations

6-1- Author Contributions

Conceptualization, F.K. and B.M.; methodology, A.Ma.; software, G.A.; validation, A.Ma., G.A., and S.A.; formal analysis, G.A.; investigation, D.G.; resources, A.Mu.; data curation, S.R; writing—original draft preparation, F.K., B.M., A.Ma., S.K., A.Mu., G.A., D.G., S.R., S.A., and A.D.; writing—review and editing, F.K., B.M., A.Ma., S.K., A.Mu., G.A., D.G., S.R., S.A., and A.D.; visualization, S.A.; supervision, A.D.; project administration, A.D. All authors have read and approved the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available in the article.

6-3- Funding

The project titled "“Cooperative platform for wheat value chain actors developed focusing on sustainable wheat production, marketing, and sale” (GCP/UZB/010/GFF)' implemented by Tashkent State Agrarian University and the Food and Agriculture Organization (FAO) of the United Nations, Uzbekistan Office.

6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Muska, A., Pilvere, I., & Nipers, A. (2025). European Green Deal Objective for Sustainable Agriculture: Opportunities and Challenges to Reduce Pesticide Use. Emerging Science Journal, 9(4), 1774–1791. doi:10.28991/ESJ-2025-09-04-02.

[2] Wheeler, T., & von Braun, J. (2013). Climate Change Impacts on Global Food Security. Science, 341(6145), 508–513. doi:10.1126/science.1239402.

[3] IPCC. (2023). Climate Change 2022 – Impacts, Adaptation and Vulnerability. Intergovernmental Panel on Climate Change (IPCC): Cambridge University Press, Cambridge, United States. doi:10.1017/9781009325844.

[4] Abumhadi, N., Todorovska, E., Assenov, B., Tsonev, S., Vulcheva, D., Vulchev, D., Atanasova, L., Savova, S., & Atanassov, A. (2012). Agricultural research in 21st century: Challenges facing the food security under the impacts of climate change. Bulgarian Journal of Agricultural Science, 18(6), 801–818.

[5] Huang, H., Legg, W., & Cattaneo, A. (2010). Climate Change and Agriculture: The Policy Challenge for the 21st Century? EuroChoices, 9(3), 9–15. doi:10.1111/j.1746-692x.2010.00174.x. (In German).

[6] Verma, K. K., Song, X. P., Kumari, A., Jagadesh, M., Singh, S. K., Bhatt, R., Singh, M., Seth, C. S., & Li, Y. R. (2025). Climate change adaptation: Challenges for agricultural sustainability. Plant, Cell & Environment, 48(4), 2522–2533. doi:10.1111/pce.15078.

[7] Abbass, K., Qasim, M. Z., Song, H., Murshed, M., Mahmood, H., & Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. Environmental Science and Pollution Research, 29(28), 42539–42559. doi:10.1007/s11356-022-19718-6.

[8] IPCC. (2022). Climate Change 2022: Mitigation of Climate Change. Working Group III Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United States. doi:10.1017/9781009157926.

[9] UNECE. (2024). Working Party on Agricultural Quality Standards. United Nations Economic Commission for Europe (UNECE), Geneva, Switzerland. Available online: https://unece.org/sites/default/files/2024-11/Programme_0.pdf (accessed on July 2025).

[10] World Bank. (2024). Climate Smart Agriculture. World Bank, Washington, United States. Available online: https://www.worldbank.org/en/topic/climate-smart-agriculture# (accessed on November 2025).

[11] Kummu, M., Heino, M., Taka, M., Varis, O., & Viviroli, D. (2021). Climate change risks pushing one-third of global food production outside the safe climatic space. One Earth, 4(5), 720–729. doi:10.1016/j.oneear.2021.04.017.

[12] World Bank. (2012). Climate-smart agriculture: a call for action. World Bank, Washington, United States. Available online: https://www.worldbank.org/content/dam/Worldbank/document/CSA_Brochure_web_WB.pdf (accessed on November 2025).

[13] Vishnoi, S., & Goel, R. K. (2024). Climate smart agriculture for sustainable productivity and healthy landscapes. Environmental Science and Policy, 151. doi:10.1016/j.envsci.2023.103600.

[14] Ma, W., & Rahut, D. B. (2024). Climate-smart agriculture: adoption, impacts, and implications for sustainable development. Mitigation and Adaptation Strategies for Global Change, 29(5), 44. doi:10.1007/s11027-024-10139-z.

[15] Partey, S. T., Zougmoré, R. B., Ouédraogo, M., & Campbell, B. M. (2018). Developing climate-smart agriculture to face climate variability in West Africa: Challenges and lessons learnt. Journal of Cleaner Production, 187, 285–295. doi:10.1016/j.jclepro.2018.03.199.

[16] FAO. (2009). Food Security and Agricultural Mitigation in Developing Countries: Options for Capturing Synergies. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. Available online: https://www.fao.org/docrep/012/i1318e/i1318e00.pdf (accessed on November 2025).

[17] FAO. (2010) “Climate-Smart” Agriculture Policies, Practices and Financing for Food Security, Adaptation and Mitigation. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. Available online: https://www.fao.org/4/i1881e/i1881e00.pdf (accessed on November 2025).

[18] Samim, S. A., Deng, X., & Li, Z. (2024). Climate-smart agricultural practices- determinants and impact on crop production. New insights from Afghanistan. Mitigation and Adaptation Strategies for Global Change, 29(8), 91. doi:10.1007/s11027-024-10178-6.

[19] Lee, C. L., Orton, G., & Lu, P. (2024). Global Meta-Analysis of Innovation Attributes Influencing Climate-Smart Agriculture Adoption for Sustainable Development. Climate, 12(11), 192. doi:10.3390/cli12110192.

[20] Zuma-Netshiukhwi, G., Anderson, J. J., Wessels, C. H., & Malatsi, E. (2025). Upscaling the Uptake of Climate-Smart Agriculture in Semi-Arid Areas of South Africa. Atmosphere, 16(6), 729. doi:10.3390/atmos16060729.

[21] Torsu, D. A., Danso-Abbeam, G., Ogundeji, A. A., Owusu-Sekyere, E., & Owusu, V. (2024). Heterogeneous impacts of greenhouse farming technology as climate-smart agriculture on household welfare in Ghana. Journal of Cleaner Production, 434, 139785. doi:10.1016/j.jclepro.2023.139785.

[22] Konfo, T. R. C., Chabi, A. B. P., Amoussouga Gero, A., Lagnika, C., Avlessi, F., Biaou, G., & Sohounhloue, C. K. D. (2024). Recent climate-smart innovations in agrifood to enhance producer incomes through sustainable solutions. Journal of Agriculture and Food Research, 15, 100985. doi:10.1016/j.jafr.2024.100985.

[23] Petros, C., Feyissa, S., Sileshi, M., & Shepande, C. (2025). Factors Influencing Climate-Smart Agriculture Practices Adoption and Crop Productivity among Smallholder Farmers in Nyimba District, Zambia. F1000Research, 13, 815. doi:10.12688/f1000research.144332.3.

[24] Aziz, M. A., Ayob, N. H., Ayob, N. A., Ahmad, Y., & Abdulsomad, K. (2024). Factors Influencing Farmer Adoption of Climate-Smart Agriculture Technologies: Evidence from Malaysia. Human Technology, 20(1), 70-92. doi:10.14254/1795-6889.2024.20-1.4.

[25] Musa, S. F. P. D., & Ariff Lim, S. (2025). Revitalising agriculture through climate change mitigation: a systematic literature review on smart technologies and sustainable practices. International Journal of Climate Change Strategies and Management, 17(1), 481–499. doi:10.1108/IJCCSM-05-2024-0071.

[26] Khasanov, S., Kulmatov, R., Li, F., van Amstel, A., Bartholomeus, H., Aslanov, I., Sultonov, K., Kholov, N., Liu, H., & Chen, G. (2023). Impact assessment of soil salinity on crop production in Uzbekistan and its global significance. Agriculture, Ecosystems and Environment, 342, 108262. doi:10.1016/j.agee.2022.108262.

[27] Abdul Razak, S. F., Yogarayan, S., Sayeed, M. S., & Mohd Derafi, M. I. F. (2024). Agriculture 5.0 and Explainable AI for Smart Agriculture: A Scoping Review. Emerging Science Journal, 8(2), 744–760. doi:10.28991/ESJ-2024-08-02-024.

[28] FAO. (2012). Developing a Climate-Smart Agriculture Strategy at the Country Level: Lessons from Recent Experience. Background Paper for the Second Global Conference on Agriculture, Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. Available online: https://www.fao.org/4/ap401e/ap401e.pdf (accessed on November 2025).

[29] Tesfaye, W., Blalock, G., & Tirivayi, N. (2021). Climate-Smart Innovations and Rural Poverty in Ethiopia: Exploring Impacts and Pathways. American Journal of Agricultural Economics, 103(3), 878–899. doi:10.1111/ajae.12161.

[30] Thornton, P. K., Whitbread, A., Baedeker, T., Cairns, J., Claessens, L., Baethgen, W., Bunn, C., Friedmann, M., Giller, K. E., Herrero, M., Howden, M., Kilcline, K., Nangia, V., Ramirez-Villegas, J., Kumar, S., West, P. C., & Keating, B. (2018). A framework for priority-setting in climate smart agriculture research. Agricultural Systems, 167, 161–175. doi:10.1016/j.agsy.2018.09.009.

[31] Saran, A., Singh, S., Gupta, N., Walke, S. C., Rao, R., Simiyu, C., Malhotra, S., Mishra, A., Puskur, R., Masset, E., White, H., & Waddington, H. S. (2024). Interventions promoting resilience through climate smart agricultural practices for women farmers: A systematic review. Campbell Systematic Reviews, 20(3), 1426. doi:10.1002/cl2.1426.

[32] Erick, S. B., Mbwambo, J. S., & Salanga, R. J. (2025). Adoption of climate-smart agricultural practices among smallholder leafy vegetable agripreneurs in semi-arid regions. A bibliometric review. Social Sciences and Humanities Open, 11, 101428. doi:10.1016/j.ssaho.2025.101428.

[33] Kabato, W., Getnet, G. T., Sinore, T., Nemeth, A., & Molnár, Z. (2025). Towards Climate-Smart Agriculture: Strategies for Sustainable Agricultural Production, Food Security, and Greenhouse Gas Reduction. Agronomy, 15(3), 565. doi:10.3390/agronomy15030565.

[34] Zheng, H., Ma, W., & He, Q. (2024). Climate-smart agricultural practices for enhanced farm productivity, income, resilience, and greenhouse gas mitigation: a comprehensive review. Mitigation and Adaptation Strategies for Global Change, 29(4), 28. doi:10.1007/s11027-024-10124-6.

[35] Okolie, C. C., Danso-Abbeam, G., Groupson-Paul, O., & Ogundeji, A. A. (2023). Climate-Smart Agriculture Amidst Climate Change to Enhance Agricultural Production: A Bibliometric Analysis. Land, 12(1), 50. doi:10.3390/land12010050.

[36] Patra, N. K., & Babu, S. C. (2023). Institutional and policy process for climate-smart agriculture: evidence from Nagaland State, India. Journal of Water and Climate Change, 14(1), 1–16. doi:10.2166/wcc.2022.024.

[37] Ritchie, H., Rosado, P., & Roser, M. (2022). Environmental Impacts of Food Production. Our World in Data.org, Geneva, Switzerland. Available online: https://ourworldindata.org/environmental-impacts-of-food (accessed on November 2025).

[38] Food and Agriculture Organization of the United Nations (FAO). (2025). Drones4Rice. Food and Agriculture Organization of the United Nations, Rome, Italy. Available online: https://dvi-ke.fao.org/digital_initiatives_details.php?id=94 (accessed on November 2025).

[39] Brears, R. (2025). Climate Smart Agriculture: Resilient Farming, Precision Technologies, and Sustainable Food Systems. Global Climate Solutions, LinkedIn, Sunnyvale, United States. Available online: https://www.linkedin.com/pulse/climate-smart-agriculture-resilient-farming-precision-brears-xoczf/ (accessed on November 2025).

[40] Tanti, P. C., Jena, P. R., Timilsina, R. R., & Rahut, D. B. (2024). Enhancing crop yields and farm income through climate-smart agricultural practices in Eastern India. Mitigation and Adaptation Strategies for Global Change, 29(5), 35. doi:10.1007/s11027-024-10122-8.

[41] Gemtou, M., Isakhanyan, G., & Fountas, S. (2025). Advancing climate-smart agriculture: Integrating technology, behavioural insights and policy for a sustainable future. Smart Agricultural Technology, 11, 100861. doi:10.1016/j.atech.2025.100861.

[42] Asante, B. O., Ma, W., Prah, S., & Temoso, O. (2024). Farmers' adoption of multiple climate-smart agricultural technologies in Ghana: determinants and impacts on maize yields and net farm income. Mitigation and Adaptation Strategies for Global Change, 29(2), 16. doi:10.1007/s11027-024-10114-8.

[43] Agyekum, T. P., Antwi-Agyei, P., Dougill, A. J., & Stringer, L. C. (2024). Benefits and barriers to the adoption of climate-smart agriculture practices in West Africa: A systematic review. Climate Resilience and Sustainability, 3(3), 279. doi:10.1002/cli2.79.

[44] Tambol, T., Derbile, E. K., & Soulé, M. (2025). Use of climate smart agriculture technologies in West Africa peri-urban Sahel in Niger. Scientific Reports, 15, 2771. doi:10.1038/s41598-024-82813-w.

[45] Omotoso, A. B., & Omotayo, A. O. (2025). Enhancing dietary diversity and food security through the adoption of climate-smart agricultural practices in Nigeria: a micro level evidence. Environment, Development and Sustainability, 27(7), 17077–17094. doi:10.1007/s10668-024-04681-8.

[46] He, R., Dai, Y., & Sun, G. (2025). How agricultural extension services affect farmers' adoption of climate-smart technology? Evidence from rural China. Journal of Environmental Planning and Management, 1–31. doi:10.1080/09640568.2025.2488013.

[47] Alemayehu, S., Ayalew, Z., Sileshi, M., & Zeleke, F. (2024). Determinants of the adoption of climate smart agriculture practices by smallholder wheat farmers in northwestern Ethiopia. Heliyon, 10(13), e34233. doi:10.1016/j.heliyon.2024.e34233.

[48] Rogers, E. (2003). Diffusion of Innovations (5th Ed.). Simon and Schuster, New York, United States.

[49] Erekalo, K. T., Pedersen, S. M., Christensen, T., Denver, S., Gemtou, M., Fountas, S., & Isakhanyan, G. (2024). Review on the contribution of farming practices and technologies towards climate-smart agricultural outcomes in a European context. Smart Agricultural Technology, 7, 100413. doi:10.1016/j.atech.2024.100413.

[50] Arshad, M., & Abdulai, A. (2025). The drivers of adoption and impact of climate-smart agricultural practices on livestock farmers' household welfare in Pakistan. Frontiers in Sustainable Food Systems, 9, 1604899. doi:10.3389/fsufs.2025.1604899.

[51] Mpinda, M. O., Bett, H. K., & Muluvi, A. S. (2025). Determinants of adoption of climate-smart agricultural practices among smallholder maize farmers in North East District, Botswana. Discover Agriculture, 3(1), 114. doi:10.1007/s44279-025-00293-6.

[52] Ferdous, Z., Anwar, M., Zahan, T., Islam, M. A., & Hossain, M. S. (2023) Climate-Smart Agriculture Technologies and Practices in Bangladesh. SAARC Agriculture Centre, Dhaka, Bangladesh.

[53] Egamberdiev, B., Zakirov, B., & Useinov, A. (2025). Fostering Resilience for Food Security in Uzbekistan. ZBW - Leibniz Information Centre for Economics, Kiel, Germany. Available online: https://hdl.handle.net/10419/318075 (accessed on July 2025).

[54] Bilal, M., Mirkasimov, B., Asfaw, E. B., Djanibekov, N., Useinov, A., Rashitova, N., Rajabova, S., & Abduvalieva, N. (2024). Potential of crop diversification to address the hidden costs of major crop value chains in Central Asia. Background paper for The State of Food and Agriculture 2024. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. doi:10.4060/cd2993en.

[55] FAO. (2023). Promotion of Iraq's agricultural extension system by supporting digital innovation and capacity development in light of the current COVID-19 pandemic. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. Available online: https://www.fao.org/3/cd1224en/cd1224en.pdf (accessed on November 2025).

[56] Karimov, A., Khalikov, B., Isaev, S., Sindarov, O., Khayitov, K., Avliyakulov, M., Isashov, A., Bulanbayeva, P., Djumanazarova, A., Muhammadov, Y., Rajabov, N., Murtazayeva, G., Kurbanov, S., Allanov, K., & Khaitov, B. (2025). Efficiency of drip irrigation in amaranth production using the HYDRUS-1D model. Frontiers in Sustainable Food Systems, 9, 1612679. doi:10.3389/fsufs.2025.1612679.

[57] Gemtou, M., Kakkavou, K., Anastasiou, E., Fountas, S., Pedersen, S. M., Isakhanyan, G., Erekalo, K. T., & Pazos-Vidal, S. (2024). Farmers' Transition to Climate-Smart Agriculture: A Systematic Review of the Decision-Making Factors Affecting Adoption. Sustainability (Switzerland), 16(7), 2828. doi:10.3390/su16072828.

[58] Khatri-Chhetri, A., Aggarwal, P. K., Joshi, P. K., & Vyas, S. (2017). Farmers' prioritization of climate-smart agriculture (CSA) technologies. Agricultural Systems, 151, 184–191. doi:10.1016/j.agsy.2016.10.005.

[59] Barua, P., & Mitra, A. (2024). Review on Climate Smart Agriculture Practice: A Global Perspective. Journal of Climate Change, 10(1), 11–20. doi:10.3233/jcc240003.

[60] Ni, L., Akramov, K., & Fan, S. (2024). Land tenure change and agricultural production and productivity in Uzbekistan. New Uzbekistan, 135–163, Routledge, United Kingdom. doi:10.4324/9781003473497-6.

[61] Abdivaitov, K., Strobl, J., & Hennig, S. (2024). Crop Rotation Current Practice and Decision-Making-A Case Study of Kumkurgan District, Uzbekistan. International Journal of Geoinformatics, 20(12), 65–76. doi:10.52939/ijg.v20i12.3777.

[62] Erdogan, C. (2020). Cotton and Products Update. Cotton and Products Annual Report UZ2020-0002. Turkey. USDA Foreign Agricultural Service (FAS), Washington, United States.

[63] World Bank. (2023). Uzbekistan - Policy Perspectives for Irrigation and Drainage Sector Reform. World Bank, Washington, United States. Available online: http://documents.worldbank.org/curated/en/099022824155511451 (accessed on June 2025).

[64] Anghelescu, A.-M., & Onel, I.-D. (2024). The EU's Green Normative Power in Central Asia. European Union Governance in Central Asia, 91–110, Routledge, United Kingdom. doi:10.4324/9781032670218-8.

[65] Nurbekov, A. (2022). Conservation Agriculture in Uzbekistan – Status and Perspectives. Agro Inform, 2, 27–32. doi:10.24412/2181-2411-2022-2-27-32.

[66] Pretty, J., Benton, T. G., Bharucha, Z. P., Dicks, L. V., Flora, C. B., Godfray, H. C. J., Goulson, D., Hartley, S., Lampkin, N., Morris, C., Pierzynski, G., Prasad, P. V. V., Reganold, J., Rockström, J., Smith, P., Thorne, P., & Wratten, S. (2018). Global assessment of agricultural system redesign for sustainable intensification. Nature Sustainability, 1, 441–446. doi:10.1038/s41893-018-0114-0.

[67] Ogisi, O. D., & Begho, T. (2023). Adoption of climate-smart agricultural practices in sub-Saharan Africa: A review of the progress, barriers, gender differences and recommendations. Farming System, 1(2), 100019. doi:10.1016/j.farsys.2023.100019.

[68] Makate, C., Makate, M., Mango, N., & Siziba, S. (2019). Increasing resilience of smallholder farmers to climate change through multiple adoption of proven climate-smart agriculture innovations. Lessons from Southern Africa. Journal of Environmental Management, 231, 858–868. doi:10.1016/j.jenvman.2018.10.069.

[69] Kassie, M., Marenya, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O., & Rahut, D. (2018). Measuring Farm and Market Level Economic Impacts of Improved Maize Production Technologies in Ethiopia: Evidence from Panel Data. Journal of Agricultural Economics, 69(1), 76–95. doi:10.1111/1477-9552.12221.

[70] Bolatova, Z., Engindeniz, S. (2020). The Economics of Climate Change in Agriculture: A Review on Kazakhstan and Turkey. Sustainable Food Chains and Ecosystems, 1-15, Springer, Switzerland. doi:10.1007/978-3-030-39609-1_1.

[71] Lou, Y., Feng, L., Xing, W., Hu, N., Noellemeyer, E., Le Cadre, E., Minamikawa, K., Muchaonyerwa, P., AbdelRahman, M. A. E., Machado Pinheiro, É. F., de Vries, W., Liu, J., Chang, S. X., Zhou, J., Sun, Z., Hao, W., & Mei, X. (2024). Climate-smart agriculture: Insights and challenges. Climate Smart Agriculture, 1(1), 100003. doi:10.1016/j.csag.2024.100003.

[72] Ali, T., Rehman, S. U., Ali, S., Mahmood, K., Obregon, S. A., Iglesias, R. C., Khurshaid, T., & Ashraf, I. (2024). Smart agriculture: utilizing machine learning and deep learning for drought stress identification in crops. Scientific Reports, 14, 30062 10 1038 41598–024–74127–8. doi:10.1038/s41598-024-74127-8.

[73] Rosenstock, T., Wilkes, A., Nowak, A., Akamandisa, V. M., Bondo, A., Kimaro, A. A., Lucas, I., Makoko, K., Masikati, P., Malozo, M., Morongwe, S., Ngwira, G., Njoloma, J., Nyoka, I., Pedzisa, T., Shoo, A., Temu, E., & Fay, J. (2018). Measurement, reporting and verification of climate-smart agriculture: Change of perspective, change of possibilities? CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Wageningen, Netherlands.

[74] Quarshie, P. T., Abdulai, S., & Fraser, E. D. G. (2023). (Re)assessing Climate-Smart Agriculture practices for sustainable food systems outcomes in sub-Saharan Africa: The case of Bono East Region, Ghana. Geography and Sustainability, 4(2), 112–126. doi:10.1016/j.geosus.2023.02.002.

[75] Billah, M. M., Rahman, M. M., Mahimairaja, S., Lal, A., Srinivasulu, A., & Naidu, R. (2025). Constraints and prospects of adoption of climate smart agriculture interventions: Implication for farm sustainability. Climate Smart Agriculture, 2(3), 100066. doi:10.1016/j.csag.2025.100066.

[76] Villalba, R., Joshi, G., Daum, T., & Venus, T. E. (2024). Financing Climate-Smart Agriculture: a case study from the Indo-Gangetic Plains. Mitigation and Adaptation Strategies for Global Change, 29, 33. doi:10.1007/s11027-024-10127-3.

[77] Falchetta, G., Semeria, F., Tuninetti, M., Giordano, V., Pachauri, S., & Byers, E. (2023). Solar irrigation in sub-Saharan Africa: economic feasibility and development potential. Environmental Research Letters, 18(9), 94044. doi:10.1088/1748-9326/acefe5.

[78] World Bank. (2024). Uzbekistan – General Water Security Assessment (English). Report 191771. World Bank Group, Washington, United States. Available online: http://documents.worldbank.org/curated/en/099062424121035288 (accessed on November 2025).

[79] Zorya, S. (2020). Recent Agricultural Growth in Uzbekistan: Assessment and Forecast (English). World Bank, Washington, United States. Available online: http://documents.worldbank.org/curated/en/515031601287108231 (accessed on November 2025).

[80] Ministry of Ecology, Environmental Protection and Climate Change of Uzbekistan (2023). National state of the environment report: Uzbekistan. International Institute for Sustainable Development, Geneva, Switzerland.

[81] World Bank. (2025). Uzbekistan – National Irrigation and Energy Efficiency Improvement Project as First Phase of the Water Efficiency and Conservation Multi-Phase Programmatic Approach (English). World Bank, Washington, United States. Available online: http://documents.worldbank.org/curated/en/099042825213520583 (accessed on November 2025).

[82] Wichelns, D., Anarbekov, O., Jumaboev, K., & Manthrithilake, H. (2010). Irrigation pricing alternatives for water user associations in Central Asia. IWMI Conference Proceedings, 211317, International Water Management Institute. doi:10.22004/ag.econ.211317.

[83] Du, Y., Liu, X., Zhang, L., & Zhou, W. (2023). Drip irrigation in agricultural saline-alkali land controls soil salinity and improves crop yield: Evidence from a global meta-analysis. Science of the Total Environment, 880, 163226. doi:10.1016/j.scitotenv.2023.163226.

[84] Sitokonstantinou, V., Porras, E. D. S., Bautista, J. C., Piles, M., Athanasiadis, I., Kerner, H., ... & Camps-Valls, G. (2024). Causal machine learning for sustainable agroecosystems. arXiv Preprint, arXiv:2408.13155. doi:10.48550/arXiv.2408.13155.

[85] Republic of Uzbekistan. (2019). Presidential Decree UP-5853 of October 23, 2019 On the approval of Development of Agriculture in the Republic of Uzbekistan for 2020–2030. Available online: https://lex.uz/en/docs/6971398?ONDATE=24.10.2019 (accessed on November 2025).

[86] World Bank. (2025). Project Appraisal Document on a Proposed Credit in the Amount of US$200 Million to the Republic of Uzbekistan for a National Irrigation and Energy Efficiency Improvement Project (P504600). Report No: PADHI00554, World Bank, Washington DC, United States.

[87] Hayward, D. (2021). Uzbekistan - Context and land governance. Land Portal Foundation, Amersfoort, Netherlands. Available online: https://landportal.org/book/narratives/2021/uzbekistan (accessed on November 2025).

[88] Kapoor, S., & Pal, B. D. (2024). Impact of adoption of climate smart agriculture practices on farmer's income in semi-arid regions of Karnataka. Agricultural Systems, 221, 104135. doi:10.1016/j.agsy.2024.104135.

[89] FAO. (2024). Smart Farming for the Future Generation. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. Available online: https://openknowledge.fao.org/items/7e4fa8d0-a963-4828-a947-ec80d55b2367 (accessed on July 2025).

[90] FAO. (2025). Successful Completion of the "Smart Farming for the Future Generation" Project: Final National Workshop. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. Available online: https://www.fao.org/countryprofiles/news-archive/detail-news/en/c/1742451 (accessed on November 2025).

[91] FAO. (2024). Digital Villages Initiative in Europe and Central Asia. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. Available online: https://www.fao.org/digital-villages-initiative/europe/fergana-villages/digital-villages-in-uzbekistan/ (accessed on November 2025).

[92] UNDP Uzbekistan. (2022). Climate Change Risks in Fergana Valley [Completed]. UNDP Uzbekistan, Tashkent, Uzbekistan. Available online: https://www.undp.org/uzbekistan/projects/completed-climate-change-risks-fergana-valley (accessed on July 2025).

[93] IIWMI. (2015). Managing irrigation-drainage systems to sustainably enhance productivity in Fergana Valley, Central Asia. International Water Management Institute (IIWMI), Colombo, Sri Lanka. Available online: https://archive.iwmi.org/wle/project/managing-irrigation-drainage-systems-sustainably-enhance-productivity-fergana-valley-central/index.html (accessed on November 2025).

[94] World Bank. (2024). Restructuring paper on a proposed project restructuring of Ferghana Valley Water Resources Management – Phase II. World Bank, Washington, United States. Available online: https://documents1.worldbank.org/curated/en/099082624024531448/pdf/P1496101ba419f0e119e931a0c4d1768072.pdf (accessed on November 2025).

[95] Berhanu, A. A., Ayele, Z. B., & Dagnew, D. C. (2024). Impact of climate-smart agricultural practices on smallholder farmers' resilience in Ethiopia. Journal of Agriculture and Food Research, 16, 101147. doi:10.1016/j.jafr.2024.101147.

[96] Ishtiaque, A., Krupnik, T. J., Krishna, V., Uddin, M. N., Aryal, J. P., Srivastava, A. K., Kumar, S., Shahzad, M. F., Bhatt, R., Gardezi, M., Bahinipati, C. S., Nazu, S. B., Ghimire, R., Anik, A. R., Sapkota, T. B., Ghosh, M., Subedi, R., Sardar, A., Uddin, K. M. Z., Khatri-Chhetri, A., Rahman, Md. S., Balwinder-Singh, & Jain, M. (2024). Overcoming barriers to climate-smart agriculture in South Asia. Nature Climate Change, 14(2), 111–113. doi:10.1038/s41558-023-01905-z.

[97] Pedersen, S. M., Erekalo, K. T., Christensen, T., Denver, S., Gemtou, M., Fountas, S., Isakhanyan, G., Rosemarin, A., Ekane, N., Puggaard, L. L., Nertinger, M., Brinks, H., Puško, D., & Adrián, J. B. (2024). Drivers and barriers to climate-smart agricultural practices and technologies adoption: Insights from stakeholders of five European food supply chains. Smart Agricultural Technology, 8, 100478. doi:10.1016/j.atech.2024.100478.

[98] Vinokurov, E., Ahunbaev, A., Chuyev, S., & Adakhayev, A. (2023). Efficient Irrigation and Water Conservation in Central Asia. Reports and Working Papers 23/4, Eurasian Development Bank, Almaty, Kazakhstan.

[99] Kannazarova, Z., Ryssalieva, L., Khamidov, S., Khamraev, K., Jaliliova, G., & Najodov, B. (2024). Management Practices for Improving Soilhealth in the Aral Sea Basin: A Case Study from Karakalpakstan. Sustainable Agriculture, 22(2), 5-8.

[100] Hermans, F., Djumanazarova, A., & Akramkhanov, A., (2023). Complete scaling readiness study of land-assisted laser levelling in Uzbekistan. International Center for Agricultural Research in the Dry Areas (ICARDA), Beirut, Lebanon.

[101] Vitón, R.; Garzaron, L.; Menza, G.; Zaccari, C.; & Dolinga, M. (2025). The state of the agri-, food-, and climate-tech innovation ecosystem in Uzbekistan. CGIAR Accelerate for Impact Platform and Valoral Advisors, Rome, Italy.

[102] Khaitov, B., Karimov, A., Khaitbaeva, J., Sindarov, O., Karimov, A., & Li, Y. (2022). Perspectives of Licorice Production in Harsh Environments of the Aral Sea Regions. International Journal of Environmental Research and Public Health, 19(18), 11770. doi:10.3390/ijerph191811770.

[103] Ualiyeva, R. M., Kukusheva, A. N., Insebayeva, M. K., Akhmetov, K. K., Zhangazin, S. B., & Krykbayeva, M. S. (2022). Agrotechnological methods of plant feeders applying for spring wheat agrocenoses – North-Eastern Kazakhstan varieties. Journal of Water and Land Development, 55(X–XII), 28–40. doi:10.24425/jwld.2022.142301.

[104] Ewulo, T. A., Akinseye, F. M., Teme, N., Agele, S. O., Yessoufou, N., & Kumar, S. (2025). Factors driving Climate-Smart Agriculture adoption: a study of smallholder farmers in Koumpentum, Senegal. Frontiers in Agronomy, 7, 1552720. doi:10.3389/fagro.2025.1552720.

[105] Finizola e Silva, M., Van Schoubroeck, S., Cools, J., & Van Passel, S. (2024). A systematic review identifying the drivers and barriers to the adoption of climate-smart agriculture by smallholder farmers in Africa. Frontiers in Environmental Economics, 3, 1356335. doi:10.3389/frevc.2024.1356335.

[106] Teklu, A., Simane, B., & Bezabih, M. (2023). Multiple adoption of climate-smart agriculture innovation for agricultural sustainability: Empirical evidence from the Upper Blue Nile Highlands of Ethiopia. Climate Risk Management, 39, 100477. doi:10.1016/j.crm.2023.100477.

[107] Zeleke, G., Teshome, M., & Ayele, L. (2024). Determinants of Smallholder Farmers' Decisions to Use Multiple Climate-Smart Agricultural Technologies in North Wello Zone, Northern Ethiopia. Sustainability, 16(11), 4560. doi:10.3390/su16114560.

[108] Geda, M. B., Haji, J., Jemal, K., & Zeleke, F. (2024). Determinants of adoption of climate smart agricultural technologies in wheat production in Arsi Zone, Oromia Region of Ethiopia. Discover Food, 4, 8. doi:10.1007/s44187-024-00077-9.

Appendix I

Climate-Smart Agriculture (CSA) Survey and Field Measurement Protocol in Uzbekistan

Introduction and Consent

Purpose: To assess the adoption of climate-smart agriculture (CSA) technologies and the associated production and environmental indicators. All responses were kept confidential and anonymized. Participation in the study was voluntary.

Informed consent: ☐ Yes ☐ No *(Terminate interview if "No".)*

Section A. Identification and Farm Characteristics

A0. Head-of-Household (HH)

A0.1 Age (years): ________

A0.2 Gender: ☐ Male (1) ☐ Female (2)

A0.3 Educational level: ☐ No education (1), ☐ Primary (2), ☐ Secondary (3), ☐ Tertiary (4), ☐ Koranic (5)

A1. City, district, village	
A2. Farm type	
A3. Farm size	
A3a. Cultivated area this season (ha)	
A4. Share of the irrigated land (%)	
A5. Main crops (share of area, %)	cotton __ / wheat __ / vegetables __ / fruits, livestock, mixed __
A6. Soil salinity (self-report or agro test)	☐ Low ☐ Medium ☐ High ☐ Unknown
A7. Years of farming experience (HH)	________
A1.1 Household size (members)	________
A1.2 Land-ownership status	☐ Owner (1) ☐ Leased (2) ☐ Inherited (3) ☐ Don't own (4)
A8. Access to credit/subsidies for CSA during the last season	☐ Yes ☐ No If Yes — program/bank: ________
Access to government funding/benefits/subsidies	

Section B. CSA Technology Adoption (reference season)

Mark practices were used and indicate scale/intensity. Include binary adoption (1/0) and scale.

Practice	Adopted (1/0)	Area / Share	Years of use / Details	Notes
B0.1 Crop rotation	□ 1 □ 0	Area (ha): __	Rotation scheme:	
B0.2 Cover crops / intercropping	□ 1 □ 0	Area (ha): __	Species: __	
B0.3 Diversification of crops	□ 1 □ 0	Minor crop share (%): __	Number of crops (≥3?): □ Yes / □ No	
B0.4 Agroforestry	□ 1 □ 0	Area (ha): __	Species/row spacing: __	
B0.5 Improved/stress-tolerant varieties	□ 1 □ 0	Share of the area (%): __	Crop: __	
B0.6 Conservation tillage (reduced/zero)	□ 1 □ 0	Area (ha): __	—	
B1. Fertilizer micro-dosing	□ 1 □ 0	Area (ha): __	Years of use: __	
B2. Organic amendments/compost	□ 1 □ 0	Area (ha): __	Rate (t/ha): __	
B6. Irrigation technology	—	Area (ha): __	☐ Drip ☐ Solar pump ☐ Surface/furrow	
B7. DSS/sensor scheduling	□ 1 □ 0	—	Water/nutrient DSS or sensors	
B8. Climate/extension services during this season	□ 1 □ 0	—	Channel: ☐ In-person ☐ Mobile ☐ Radio ☐ Other: __	

Section C. Production Practices

C1. Nutrient application rates (kg/ha) —	N __ / P_2O_5 __ / K_2O __
C1. Nutrient application rates (kg/ha) —	N __ / P_2O_5 __ / K_2O __
C2. Sowing dates (dd.mm)	Cotton __ ; Wheat __
C3. Number of irrigation (per season)	Cotton __ ; Wheat __
C4. Mechanization	☐ Own machinery ☐ Rented ☐ None

Section D. Socioeconomic indicators and perceptions

D1. Labor employed	__
D2. Crop income last season (USD/ha)	Cotton __ ; Wheat __Other
D3. Membership in cooperatives/associations	☐ Yes ☐ No
D4. Perceived climate change and variability	☐ Yes (1) ☐ No (0)
D5. Access to climate advisory information (12 months)	☐ Yes (1) ☐ No (0) — Channel: ☐ Extension ☐ SMS/app ☐ Radio/TV ☐ Farmer group ☐ Other: __

Section E. Risk Perceptions and General Barriers

E1. Top barriers to CSA (choose up to three): ☐ Capital costs, ☐ Technical complexity, ☐ Information/skills deficit, ☐ Water limits, ☐ Institutional constraints, ☐ Other: ________

E2. Willingness to scale CSA if a 20% CAPEX subsidy is offered: ☐ Yes ☐ No ☐ Unsure

Section E2. Cultural Perceptions, Knowledge, and Institutional Constraints (Less-popular technologies: CC, and SI)

Use Likert 1–5, where 1 = strongly disagree/unfamiliar and 5 = strongly agree/deep knowledge.

E2.1 Awareness — Familiarity with CC (1–5)	__ ; Sources: ☐ Neighbors ☐ Extension ☐ Demo ☐ Dealer ☐ Media ☐ NGO ☐ Other: __
E2.1 Awareness — Familiarity with SI (1–5)	__
E2.2 Norms — "CC is not customary" (1–5)	__ ; SI is not customary (1–5): __ ; Leaders approve CC/SI (1–5): __
E2.2 Norms — Calendar conflict (1–5) and Reputation concern (1–5)	__ ; __
E2.3 Knowledge/Self-efficacy/ Know CC species (1–5)	__ ; Know CC calendar (1–5): __ ; Can size SI (1–5): __ ; Can operate/maintain SI (1–5): __ ; Can access advice (1–5): __
E2.4 Institutional — Land tenure (Yes/No; severity 1–5)	__ ; Quota constraints (Yes/No; severity 1–5): __ ; Water-rotation misaligned (Yes/No; severity 1–5): __ ; Market/certification barriers (Yes/No; severity 1–5): __ ; Service/parts (SI) (Yes/No; severity 1–5): __ ; Import/credit (SI) (Yes/No; severity 1–5): __
E2.5 Practical obstacles — CC	☐ Seed availability ☐ Specialized equipment ☐ Timing conflicts ☐ Pest/disease risk ☐ Knowledge gap ☐ Other: __ ; Perceived income risk (1–5): __
E2.5 Practical obstacles — SI	☐ Feasibility study ☐ Theft/vandalism ☐ Winter/overcast performance ☐ Lack of service ☐ Other: __ ; Perceived income risk (1–5): __
E2.6 Intention — Plan to adopt within 12 months	CC: ☐ Yes ☐ No ☐ Unsure; SI: ☐ Yes ☐ No ☐ Unsure; Conditions: ☐ ≥20% CAPEX subsidy ☐ ≥5% price premium ☐ Free training ☐ Local demo ☐ Service ≤30 km ☐ Other: __

Section F. Field Measurements (to be completed by the researcher)

F1. Soil erosion (visual score 0–5)	__ (0 = no evidence; 5 = severe rill/gully). Method: visual scoring + micro-relief (cm)
F2. Water quality (peak irrigation)	pH __ ; EC (μS/cm) __ ; NO_3^- -N (mg/L) __ ; TDS (mg/L) __ ; Sampling point: ☐ Main canal ☐ Field ditch ☐ Well
F3. Phenological observations	BBCH stage __ ; canopy cover (%) __ ; plant height (cm) __

Section G. Yields (last season)

G1. Cotton yield (t/ha): __ Source: ☐ farm books ☐ weighing ☐ estimate

G2. Wheat yield (t/ha): __ Source: ☐ farm books ☐ weighing ☐ estimate

Section H. Follow-up

H1. Willing to participate in follow-up verification visits: ☐ Yes ☐ No Contact: ________

Section I. Analytical Questions

I1. Selection bias and performance bias

I1.1 Average yields over last 3 seasons before current adoption — Cotton/Wheat (t/ha)	Cotton __ ; Wheat __ (source: records if available)
I1.2 Agreement (1–5): My pre-adoption performance influenced my decision to adopt multiple CSA technologies.	__
I1.3 Access to extension before adoption (visits/month)	__ ; Access to credit before adoption: ☐ Yes ☐ No
I1.4 Counterfactual this season if not adopted	☐ Lower ☐ Same ☐ Higher ☐ Unsure

I2. Scalability of fertilizer micro-dosing returns

I2.1 Current farm size (ha); area under micro-dosing (ha); feasible expansion for the next season (ha)	__ ; __ ; __
I2.2 Main constraints to micro-dosing scaling (up to 3)	☐ Labor ☐ Training/supervision ☐ Input supply/logistics ☐ Measurement/precision equipment ☐ Record-keeping ☐ Other: __
I2.3 Estimated ROI at the current scale (%)	__ ; Expected ROI if scaled to ≥80% of arable area: ☐ Increases ☐ Unchanged ☐ Decreases ☐ Unsure — Reason: __

I3. Potential negative side effects (including nutrient losses)

I3.1 Side effects observed?	☐ Yes ☐ No — If Yes: ☐ Nitrate leaching ☐ Pest/disease shifts ☐ Lodging ☐ Soil crusting ☐ Other: __
I3.2 Mitigation practices	☐ Split applications ☐ Buffer strips/grass waterways ☐ Cover crops ☐ Adjusted irrigation scheduling ☐ Soil testing/calibration ☐ Other: __
I3.3 Are water-quality test results available (last 12 months)?	☐ Yes (attach) ☐ No

I4. Longitudinal study participation and expectations

I4.1 Consent to be tracked over multiple seasons	☐ Yes ☐ No
I4.2 Expected learning effects over time (1–5) and expected adaptation (brief)	__ ; __
I4.3 Seasonal shocks that could alter year-to-year outcomes	☐ Yes ☐ No — Specify: __

I5. Policy feasibility within current agricultural governance (cotton/wheat quota and water schedules)

I5.1 Do delivery obligations/quotas limit rotation change or cover crops?	☐ Yes ☐ No ☐ Not applicable — Explain: __
I5.2 Are water-allocation schedules compatible with CSA timing (e.g., cover crops, fertigation)?	☐ Yes ☐ No ☐ Partly — Details: __
I5.3 Feasibility on your farm under current policies (1 very infeasible – 5 very feasible)	(a) Micro-dosing __ ; (b) Cover crops __ ; (c) Drip/solar irrigation __ ; (d) Conservation tillage __ ; (e) DSS/sensors __
I5.4 Most helpful policy instruments (select up to 3)	☐ CAPEX subsidies ☐ Input vouchers ☐ Guaranteed market/premium ☐ Irrigation schedule flexibility ☐ Extension/mentoring ☐ Low-interest credit ☐ Tax incentives ☐ Other: __