Collaborative systems thinking analysis for enhancing climate smart agricultural (CSA) technology adoption in Africa

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Abstract

Agricultural technology adoption is a critical driver of sustainable development, particularly in developing regions where agriculture plays a pivotal role in food security and livelihoods. This study combines network analysis, including causal loop diagrams (CLD), with centrality metrics, to uncover key leverage points within the system where targeted interventions can yield significant impacts on climate smart agricultural (CSA) technology adoption. Our findings reveal the intricate interconnections among various determinants, emphasizing the non-linear nature of technology adoption processes. The degree of centrality analysis identifies influential determinants within the network, offering insights into their potential impact and importance in driving change within the broader system. This research offers valuable guidance for policymakers, agricultural extension services, and development practitioners involved in CSA. It contributes to the efficient adoption and implementation of relevant technologies, thereby enhancing the resilience of agricultural practices in the face of climate change. Furthermore, it underscores the importance of considering the holistic context and intricate interactions to promote sustainable agricultural development in developing regions.

Keywords: System dynamics, network analysis, causal loop diagram, feedback loops, Interconnections

Introduction

Climate change poses a formidable challenge to agriculture in Africa, a continent where the agrarian sector is not only the backbone of its economies but also a cornerstone of its food security, economic growth, and cultural heritage. The intricate relationship between climate change and agricultural productivity in Africa is increasingly becoming a focus of scientific and policy discussions [1][2][3]. This is primarily because the African continent, despite contributing minimally to global greenhouse gas emissions, is disproportionately affected by the adverse impacts of climate change [4] (Almaraz et al., 2023). The dependence of African agriculture on rain-fed systems makes it particularly vulnerable to climate variability and change [5]. Fluctuations in rainfall patterns and increased temperatures have been linked to reduced crop yields, exacerbating food insecurity in a continent where a significant portion of the population is already undernourished [6] [5]. For instance, studies predict that major cereal crops in Africa will experience a reduction in yield of up to 20% by 2050 due to climate change [7][8]. Moreover, the impact of climate change on agriculture extends beyond food production. It influences economic stability, as the agricultural sector is a major employer and a critical source of income for the vast majority of the rural population in Africa [9]. In addition, agriculture in Africa is deeply intertwined with cultural practices and traditions, playing a vital role in the social fabric of communities [10]. Climate change-induced alterations in agricultural practices can, therefore, have profound cultural implications. To tackle these complex challenges, there is an urgent requirement for adaptive strategies that not only alleviate the effects of climate change but also bolster the agricultural sector's resilience. It is crucial to examine the transformative potential of Climate-Smart Agriculture (CSA) in Africa, particularly concerning its fundamental principles. This examination is essential to gain insights into how CSA can actively contribute to sustainable development, food security, and climate resilience across the continent [11][2].

The pillars of CSA establish a comprehensive framework essential for transforming and reorienting agricultural systems to foster development and ensure food security in a changing climate [12]. The first pillar, sustainably increasing agricultural productivity and incomes, emphasizes enhancing food production and farmers' livelihoods in an environmentally sustainable way. This goes beyond just boosting yields; it involves improving resource use efficiency and minimizing environmental impacts [13][14]. The second pillar focuses on adapting and building resilience to climate change, a critical aspect for managing risks associated with climate variability and extreme weather events [3][15]. It encompasses the development and deployment of farming practices that are resilient to climatic stresses [16] [3]. Lastly, the third pillar is about reducing and/or removing greenhouse gas emissions. This includes implementing farming methods and technologies that lower emissions, as well as practices like agroforestry that enable agriculture to act as a carbon sink [11]. Together, these pillars aim to create an agriculture sector that is productive, resilient, and a contributor to climate change mitigation.

Climate-smart agriculture technologies (Figure 1) in Africa encompass a range of innovative and traditional practices tailored to enhance agricultural resilience and sustainability in the face of climate change. Key among these are drought-resistant and early maturing crop varieties, crucial in regions facing erratic rainfall and prolonged dry spells [17]. These varieties are bred to withstand adverse climatic conditions while ensuring timely harvests, thereby securing food production and livelihoods [17][18]. Improving soil health is another critical aspect, achieved through conservation agriculture practices such as minimum tillage, cover cropping, and crop rotation [17][18]. These techniques not only enhance soil fertility and structure but also improve water retention, making crops more resilient to climate extremes. Water management, is integral to CSA in Africa. Techniques like rainwater harvesting, where small dams and reservoirs collect and store rainwater, alongside efficient irrigation systems like drip irrigation, ensure optimal water usage, crucial in drought-prone areas [16] [18]. Agroforestry, which involves integrating trees with crop and animal farming, offers multifaceted benefits. It improves soil health, provides shade and shelter, acts as windbreaks, and aids in carbon sequestration, while also diversifying income sources through the harvesting of fruits, nuts, and timber [19]. Access to climate information and early warning systems is also vital [20]. Leveraging mobile technology and community networks, farmers receive timely updates on weather patterns, pest outbreaks, and market conditions, enabling better planning and response to climatic risks [21]. Lastly, renewable energy technologies like solar-powered irrigation pumps and biogas systems are gaining traction [22]. These reduce the reliance on fossil fuels and lower greenhouse gas emissions, providing sustainable energy sources to rural communities. Together, these CSA technologies represent a holistic approach to transforming agriculture in Africa, making it more productive, resilient, and environmentally sustainable.

Figure 1. Illustration of climate-smart agriculture (CSA) for smallholder farmers in Africa, featuring the utilization of smartphones to access climate information services (CIS). This illustration showcases the integration of technology with sustainable farming practices, incorporating natural pest control and organic fertilization within a dynamic rural farmland setting. Additionally, wind and solar energy systems are seamlessly integrated to support irrigation

The integration of CSA practices among small-scale farmers is critical for sustainable agricultural development. Yet, studies by [23] [24] [25] report low adoption rates, raising concerns about the effectiveness of current strategies. Traditional research methods, focusing on the direct factors influencing adoption through univariate and multivariate analyses, fall short by not considering the intricate web of technology, gender dynamics, socioeconomic conditions, educational backgrounds, and national policies. This oversight, as argue in [26], limits the ability of the 'triple-win' CSA model to address the complex social dynamics at play and the prevailing conditions that sustain conventional development practices. The call for systems thinking, as advocated by [27] highlights the importance of a comprehensive approach that examines the interconnectedness of these factors, thereby offering insights into the systemic barriers and opportunities for CSA adoption. This perspective not only aids in understanding the broader system dynamics but also guides the development of more effective, inclusive, and sustainable policy interventions.

This study aims to provide a comprehensive overview of how CSA could serve as a beacon of hope for the African continent, fostering sustainability and resilience in the face of climate change. We hypothesize that, CSA, by incorporating innovative farming techniques, effective resource management, and cutting-edge technologies, provides a promising path in a region grappling with climate variability, resource depletion, and escalating food insecurity [16] [18]. Our analysis strives to provide a comprehensive perspective on how the adoption of CSA not only mitigates the impacts of climate change but also enhances agricultural productivity, livelihoods, and ecosystem health within the African context. Furthermore, we establish a basis for examining policy frameworks, community engagement, and the scalability of CSA practices, thereby offering valuable insights for a wide range of stakeholders, ranging from local farmers to global policymakers. The aim is to initiate a dialogue about the imperative need for the integration of climate-smart strategies in African agriculture, paving the path towards a future where environmental sustainability and economic prosperity coexist harmoniously.

Materials and methods

Collaborative system thinking workshop for unlocking climate smart agriculture technology adoption.

To advance understanding of CSA adoption dynamics, a systems thinking methodology was applied, utilizing CLD for qualitative insights. A three-day workshop in Cotonou, Benin, from September 27 to 29, 2023, brought together 33 researchers, including 9 women, from diverse academic backgrounds. Participants hailed from three Beninese universities (University of Abomey-Calavi, University of Parakou, and National University of Agriculture), the National Institute of Agricultural Research (INRAB), and international bodies like the International Institute of Tropical Agriculture (IITA) and the International Centre of Insect Physiology and Ecology (*icipe*). The presence of Ghanaian experts from Crops Research Institute of the Council of Scientific and Industrial Research (CSIR/CRI), the University of Development Studies (UDS), and the Kwame Nkrumah University of Science and Technology (KNUST) enriched discussions, promoting an intercultural and interdisciplinary examination of CSA practices. The invited experts came from varied fields such as crop science, sociology, environmental science, animal sciences, forestry, natural resources, agronomy, pest management, and held specialized knowledge in areas like modeling, gender studies, systems thinking, One Health, and climate-resilient agriculture. This multidisciplinary gathering was crucial for collecting comprehensive data and insights on the multifaceted aspects of CSA implementation and its impacts.

During the workshop, an essential focus was placed on training the researchers to ensure they had a thorough understanding of key concepts, enabling them to contribute effectively to the discussions. The training encompassed key areas including climate-smart agriculture, One-Health, system thinking approach, and system dynamics modelling. This foundational knowledge was crucial for participants to effectively analyze and discuss the factors involved in the adoption of CSA practices and the interconnections between these factors. After establishing a common ground in understanding these concepts, the workshop shifted its focus to the critical issue of long-term adoption of CSA practices. The team engaged in in-depth discussions to unravel and conceptualize the complexities of this problem. Following this, they were divided into three groups, with each group tasked to identify and list all factors influencing the adoption of climate-smart technologies. In a comprehensive plenary session, each group presented their findings, providing clear definitions for each identified factor. This session was instrumental in achieving a consensus among all participants on the definitions, transforming these factors into well-defined variables. Subsequently, the plenary session engaged in a collaborative process to select the most relevant variables. These were then grouped into distinct components or subsystems, enabling a more structured and systematic approach to understanding the multifaceted nature of CSA adoption. This collective effort laid the groundwork for developing a more nuanced and comprehensive understanding of the dynamics involved in the adoption of CSA technologies.

In the workshop's second phase, the emphasis shifted towards constructing a guide model, a collaborative process that engaged the entire team in establishing connections among the previously identified variables. This process began with identifying the outcomes and drivers related to CSA technology adoption. Once these elements were defined, a foundational model was created, focusing on the primary drivers and outcomes. Participants were then guided to systematically establish causal links between these variables, using arrows to depict the direction and nature of their influence – whether positive or negative

Ethics statement

This study adhered to the ethical standards outlined in the 1964 Declaration of Helsinki and its subsequent revisions. Given the retrospective nature of this research, which relied on anonymized data analysis, formal consent from participants was not sought. This approach was adopted because the study presented no discernible risks to the participants and preserved complete anonymity throughout all stages of the research. The research procedure is consistent with the guidelines established by the Ethics Committees of the respective institutions involved, assuring the safeguarding of participants' information and the maintenance of ethical research principles.

System thinking model development procedure

Understanding and constructing the cause-effect relationships between various elements is a critical step in developing a holistic analysis of complex systems, especially in the context of climate-smart agricultural technology adoption [28][29]. The modeling process began with the development of causal loop diagrams (CLD) for each individual subsystem. These diagrams were later synthesized to form a comprehensive representation of the entire complex system governing the adoption of CSA technologies. A crucial step in this process was the identification of feedback loops within the CLDs. Feedback loops are fundamental in systems thinking as they illustrate how variables interconnect and influence each other, either amplifying (reinforcing loops) or balancing (balancing loops) the system dynamics. In the CLD, each cause-effect relationship is assigned an appropriate polarity, either positive or negative, to accurately represent the nature of the interactions. Positive relationships indicate that an increase in one variable leads to a corresponding increase in another. Conversely, negative relationships suggest that an increase in one variable results in a decrease in the other. This distinction is fundamental in understanding the behavior of complex systems, as it reveals how various elements influence each other either directly or inversely. The aggregation of these causal relationships, whether positive or negative, gives rise to feedback loops. These loops are crucial in systems thinking as they determine the system's behavior over time. Feedback loops can be either negative (balancing) or positive (reinforcing), as explained by [27]. Balancing feedback loops act to resist changes in the system, maintaining stability and equilibrium. On the other hand, reinforcing feedback loops amplify changes, either contributing to rapid growth or decline in the system. As noted by [30], these loops are instrumental in understanding how systems respond to internal and external pressures, ultimately shaping their trajectory.

The CLD for the complex system of CSA technology adoption was developed, drawing upon a rich amalgamation of sources and expertise. The foundation for this CLD was laid through a review of relevant literature, encompassing published articles, authentic information from credible websites, and comprehensive government reports [31][32][19]. This diverse pool of resources ensured that the CLD was both comprehensive and grounded in current, authoritative knowledge.

- In the initial phase of the CLD's development, the core research problem was clearly defined. This step was critical for guiding the subsequent identification of key variables that are crucial in understanding the dynamics of technology adoption in the context of CSA. These variables were selected to represent the critical elements within the system, ensuring that the CLD would capture the essential aspects and intricacies of technology adoption.
- Once the key variables were identified, the process of developing the CLD commenced. This involved connecting the variables with links, each marked with the appropriate polarity signs – positive or negative – to accurately depict the nature of their

relationships. The construction of the CLD was not just about mapping these individual relationships, but also about identifying and connecting several feedback loops.

- The creation of the CLD was facilitated by the use of the VENSIM modelling platform [33], a tool that enables the detailed and precise modelling of complex systems. The utilization of VENSIM allowed for a more structured and visual representation of the relationships and feedback loops, thereby enhancing the clarity and comprehensibility of the model.

Network analysis of the causal loop diagram (CLD)

The developed CLD for climate smart agricultural technology was converted into a directed adjacency matrix, encompassing 39 variables that represented the nodes. These nodes formed the 39 key determinants of the system, and their interconnections resulted in 139 edges, which were utilized to construct the adjacency matrix A_{ij} [34]. This transformation into a matrix format facilitated a quantitative analysis of the network's properties. Key network properties such as the density, average path length, and modularity of the matrix were determined, providing insights into the structural characteristics of the technology adoption network. The density of the network, for instance, indicated how interconnected the various determinants were within the system. The average path length represented the mean distance between the shortest paths of all pairs of vertices, shedding light on the network's connectivity.

To evaluate the impact of individual determinants within the network, several measures of centrality were calculated. These included the degree of centrality (K), which indicates the number of connections a determinant has, encompassing both incoming and outgoing links [35]. The formulae for degree-in (K^{in}) and degree-out (K^{out}) for each determinant are derived using the adjacency matrix A_{ij} [36]. This degree of centrality offers a view of the local influence of a determinant within its immediate network. Closeness centrality (C) and betweenness (B) were also computed, providing further insights into how determinants are positioned within the network. Additionally, PageRank centrality or node strength (X) was determined, estimating the overall influence of certain determinants on the entire network [37][36].

The degree of centrality within a network is a crucial metric that reflects the number of connections a determinant has, encompassing both the incoming and outgoing links associated with each determinant [35]. In the context of our network analysis, this measure is computed by summing the connections leading to the determinant and those originating from it. This calculation is made in relation to the Adjacency matrix A_{ij}, which maps the interactions between different determinants. For a given determinant, the degree-in (K^{in}) is determined by Equation (1), which sums all incoming connections to that determinant. Conversely, the degree-out (K^{out}) is calculated using Equation (2), aggregating all outgoing connections from the determinant. These calculations, as outlined by [36], provide a clear quantitative measure of how interconnected each determinant is within the network.

$$K_i^{in} = \sum_{j=1}^{N} A_{ij} \tag{1}$$

$$K_j^{out} = \sum_{i=1}^{N} A_{ij} \tag{2}$$

$$K = K_i^{in} + K_j^{out} \tag{3}$$

Closeness centrality (C) in network analysis is a measure that calculates the proximity among determinants, identifying which ones are more efficient in spreading information throughout the network. It quantifies a determinant's relationship to all other determinants in the network, taking into account not just direct but also indirect connections from that determinant [35].

While degree centrality provides a local measure within the network, closeness centrality offers a global perspective of a determinant's impact on the network. A high closeness value indicates that a specific determinant has a short average distance to all other determinants in the network, suggesting its central role. Determinants with high closeness centrality can be quickly affected by changes in any part of the network and, in turn, can rapidly effect changes in other parts [37][36]. This centrality is determined by measuring the mean distances from one determinant to all others, with the point having the lowest mean distance being the most central in the network.

Betweenness centrality (B) refers to the frequency with which a node appears on the shortest paths between pairs of other nodes in the network. It is indicative of a node's importance in the average pathways connecting other pairs of determinants, illustrating its intermediary role [37][36]. A determinant with a high frequency of occurrence on these paths plays a crucial role in the network, acting as a key connector or bridge between other determinants [35]. Such a point can control the flow of information, forming a structural hole in the network. Determinants with high betweenness centrality fill many of these structural holes. Interestingly, a node can have high betweenness centrality even if it is not central in terms of local degree or global closeness, yet still play a significant role in the overall network structure [35].

In the context of the adoption of CSA technologies, PageRank centrality is used to assess which determinants (nodes) in the network are most influential. These determinants might not necessarily have the most connections (as measured by degree centrality), but they are crucial in the network due to their connections to other significant nodes. For instance, a determinant that is connected to several key influencers in the network would have a high PageRank score, signifying its importance in the overall dynamics of technology adoption. The calculation of PageRank involves an iterative process. It begins with an arbitrary assignment of importance to each node and then repeatedly adjusts these values based on the central premise that a node's importance is derived from the importance of the nodes that link to it. The process continues until the importance values converge to a stable state, at which point the PageRank values can be interpreted. The comprehensive analysis of the developed matrix, including the calculation of closeness and betweenness centralities, was conducted using R studio software [38].

Results

System model of climate smart agriculture technology adoption

In applying systems thinking to the study of technology adoption, a comprehensive analysis was conducted to identify the key variables influencing this process. This analysis revealed a total of 132 interactions among 40 distinct variables. These interactions gave rise to 34 feedback loops within the system, which were comprised of 25 positive (reinforcing: R) and 9 negative (balancing: B) loops. These loops play a crucial role in capturing the essential components and dynamics of the entire system, as illustrated in Figure 2. The CLD that emerged from this analysis includes both reinforcing and balancing loops, as well as driving factors. These elements are instrumental in elucidating how the variables are interconnected, thus creating a balance within the system. The reinforcing loops (R) serve to amplify changes within the system, whereas the balancing loops (B) act to moderate these changes, helping to maintain system stability. For a more structured and detailed understanding, the technology adoption system was subdivided into 5 main sub-systems:

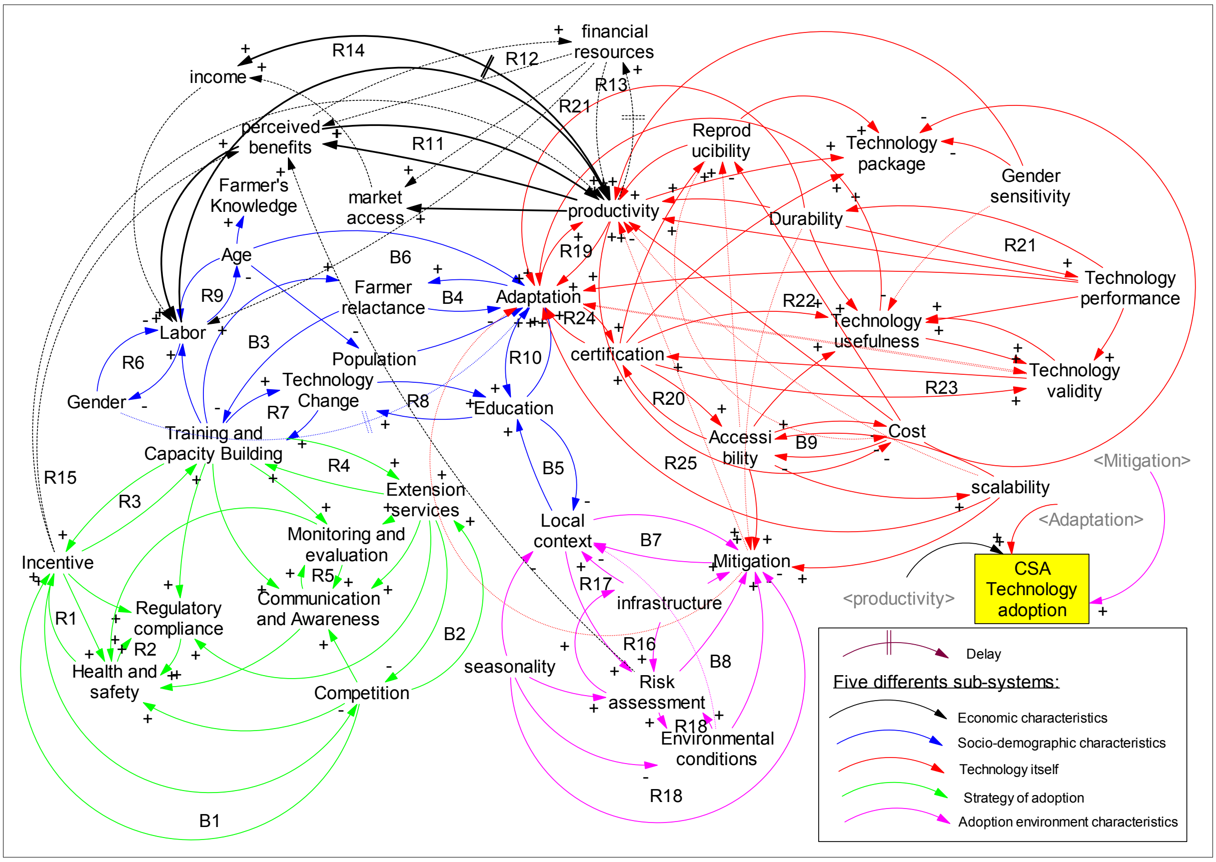

Figure 2. Causal Loop Diagram (CLD) that depicts the complexities involved in the adoption of climate smart agricultural (CSA) technology. This diagram illustrates the intricate network of variables and their interrelationships, highlighting the feedback loops – both reinforcing and balancing – that drive the dynamics of technology adoption in the context of CSA. The CLD serves as a visual map, aiding in the understanding of how various elements within the economic, socio-demographic, technological, environmental, and strategic systems interact and influence the overall process of adopting climate smart agricultural technologies.

1. ***Economic system:*** This sub-system encompasses variables related to the financial aspects of technology adoption, such as costs, benefits, and economic incentives.
2. ***Socio-demographic characteristics:*** This includes variables like education levels, community norms, and demographic factors that influence technology adoption.
3. ***Technology system:*** This focuses on the specifics of the technologies themselves, including their accessibility, usability, and adaptability.
4. ***Environment system:*** This sub-system considers the environmental factors that affect or are affected by technology adoption, such as climate patterns and land use.

5. ***Strategy system:*** This involves variables related to the strategies and policies that influence technology adoption, including government policies, extension services, and institutional support.

This approach resulted in the development of a detailed CLD, represented in Figure 2, which provides a visual and analytical representation of the complex interactions and feedback loops within and across these 5 sub-systems. Each variable is linked to others through a series of cause-and-effect relationships, represented by arrows in the diagram. Table 1 elaborates on these loops for each component, detailing the specific variables involved and how they interact to either balance or reinforce aspects of CSA technology adoption.

Table 1: Causal loop diagram description

Loop	**Description**	**Implication**
	Strategy Adoption	
R1	Incentive-Health and safety-Incentive	Promoting incentives positively impacts health and safety
R2	Regulatory compliance-Health and safety-Regulatory compliance	Complying to regulations set will improve health and safety of users of the technology
R3	Incentive-Training and Capacity Building-Incentive	Incentives can be a motivation that positively impacts training and capacity building
R4	Extension Services -Training and Capacity Building-Extension Services	Increasing extension services offer more time for training and capacity building. Training and Capacity Building can increase the provision of extension services
R5	Monitoring and Evaluation-Communication and Awareness-Monitoring and Evaluation	Monitoring and evaluation positively impacts communication and awareness by quantifying communication effectiveness
B1	Incentive-competition-Incentive	Incentives reduce the competition of a certain technology in an area
B2	Extension Services – Competition – Extension services	Additional services offered for a technology will decrease competitive ability of other technologies
	Socio-demographic Characteristics Component	
R6	Gender-Labor-Gender	Gender has a negative impact on labor provision. Certain tasks can only be achieved by a specific gender and likewise gender can influence productivity of a task.
R7	Training and Capacity Building-Technology Change-Training and Capacity Building	Training and Capacity Building has a positive impact on technology change as people adopt motiving more training to better understand the technology
R8	Technology Change-Education-Technology Change	Changing technology creates opportunities for further education. Further education results in updates or improvements on the technology.
R9	Age-Labor-Age	Provision of labor for various task often have an age requirement for better chances of accomplishment.
R10	Education – Adaptation – Education	Increasing the education level of the people will promote easier adaptation of the technology.
B3	Farmer reluctance -Training and Capacity Building-Farmer reluctance	Reluctance by farmers to adopt a technology will discourage any training provided. Increasing trainings will

		reduce reluctance encountered due to lack of understanding of the technology.
B4	Farmer reluctance-Adaptation-Farmer reluctance	Adaptation of a technology will not be successful if the farmers to use it aren't willing to accept. However increased adaptation will cause a change in the farmers' perspective on the technology
B5	Education-Local context-Education	Education awareness of a technology reduces the local context or assumptions formed.
B6	Labor – Age -Adaptation-Education-Technology change-Training and Capacity Building-Labor	Labor and age of the local population will influence the extent of adaptation of a technology in that locality.
R11	Productivity-Perceived benefits -Productivity	Increasing production of the technology increases the benefits to be acquired upon successful adaption.
R12	Perceived benefits-Financial resources - Perceived benefits	Benefits to be acquired are a motivating factor for more financial resources to be used
R13	Productivity-Financial resources -Productivity	High productivity will result in high expenditure. Increase in expenditure will likewise increase productivity.
R14	Labor – Productivity – Income – Labor	Availability of labor increases production of the technology thus more income generated to hire more employees.
R15	Incentive-Productivity-perceived benefits-Incentive	Incentives encourage productivity which in turn increase perceived benefits received
	Adoption Environment Component Feedback Loops	
R16	Risk assessment-infrastructure-Risk assessment	Assessing the risk involved in infrastructure ensures better realization of the technology. Increase in infrastructure increases assessments done on the adaptation and adoption of the tech.
R17	Local Context - Risk assessment -Infrastructure-Local context	The local context influences what assessments to be done on the infrastructure so that the technology is locally adopted.
R18	Environmental conditions - Risk assessment - Environmental conditions	The environmental conditions influence how much risk will be undertaken for successful adaptation of a technology.
B6	Mitigation-Local context -Mitigation	Carrying out mitigation actions can cause negative response from the locality.
B7	Environmental conditions – Risk assessment-Mitigation-Environmental conditions	An assessment of the environment will give directions on which mitigation to be undertaken.
	Technology Component Feedback Loops	
R19	Adaptation-Productivity-Adaptation	A given technology will increase productivity if it has been adapted by the set target.
R20	Accessibility-Certification-Accessibility	Increasing accessibility of a technology will have to increase its certification to enhance its acceptability.
R21	Durability-Tech performance-Durability	Durability of a tech will greatly determine the output with respect to the intended functions of the technology.
R22	Tech usefulness-Adaptation-Certification-Tech usefulness	Tech usefulness influences adaptation which positively impacts certification of a certain technology
R23	Certification-Tech validity-Certification	Certification increases the tech validity of a certain technology in the market
R24	Adaptation-Certification-Adaptation	Adaptation of a technology will increase the chances of certification
R25	Adaptation-Certification-Accessibility-Scalability-Adaptation	Adaptation influences certification which increases accessibility and scalability of the technology
B9	Accessibility-Cost-Accessibility	The easier the technology is the lower the cost incurred. However high prices will discourage expenditure on the technology.

The strategy of adoption subsystem

The subsystem analysis within the context of CSA technology adoption highlighted the critical importance of regulation and compliance and health and safety factors in ensuring successful implementation (as depicted in Figure 2). These components are integral to the framework that governs and guides the adoption process, ensuring that it aligns with both legal standards and safety norms. Key to this process are the factors of training and capacity building and communication and awareness. These elements are vital for equipping stakeholders with the necessary skills and knowledge to effectively implement CSA technologies. Training and capacity building ensure that farmers and other stakeholders are well-versed in the nuances of CSA technologies, while communication and awareness efforts help in disseminating information and promoting understanding among the broader community. These efforts are often facilitated by extension services, which play a pivotal role in bridging the gap between technology providers and end-users. These services make the strategy more accessible, incentive-driven, and competitive, thereby enhancing the appeal and feasibility of adopting CSA technologies. Another crucial aspect of the strategy is its sustainability, which is upheld through monitoring and evaluation. This process ensures that the implementation of CSA technologies is not only effective in the short term but also adaptable and resilient over the long term, capable of withstanding various challenges and evolving with changing circumstances.

The causal loops analysis, presented in Table 1, further elucidates these dynamics. It identifies 5 reinforcing loops and 2 balancing loops within the system. The reinforcing loops highlight processes that amplify the effectiveness of the strategy, such as how increased training leads to better implementation, which in turn encourages more training. On the other hand, the balancing loops represent self-regulating mechanisms that help maintain the stability of the system, such as checks and balances in regulation and compliance ensuring that health and safety standards are not compromised in the pursuit of technology adoption.

Socio-demographic characteristics subsystem

The analysis of the socio-demographic component in the context of CSA technology adoption revealed several key characteristics that are instrumental in determining the success of these technologies. As depicted in Figure 2, these include the adaptability of farmers to new technologies, their knowledge and understanding of these technologies, and the availability of labor. These characteristics are influenced by various factors such as the age and gender demographics of the population, the level of capacity building and education provided, and the local context in which the farmers operate. A critical element in facilitating these factors and, by extension, enhancing the key characteristics for successful adoption, is the role of technology champions. These champions are pivotal in reducing farmers' reluctance towards new technologies. They achieve this through targeted efforts in capacity building and education, directly addressing the knowledge gaps and apprehensions that farmers may have.

The interplay of these variables within the socio-demographic subsystem of CSA technology adoption is further illustrated in the causal loops analysis. This analysis, presented in Table 1, identified 5 reinforcing loops and 4 balancing loops. The reinforcing loops represent the positive feedback mechanisms where variables such as increased education and effective capacity building lead to greater knowledge and adaptability among farmers, which in turn encourages further educational and capacity-building efforts. On the other hand, the balancing loops act as regulatory mechanisms, ensuring that the influence of socio-demographic factors does not lead to negative outcomes, such as overdependence on external support or neglect of local context and traditional knowledge.

The economic characteristics subsystem

The analysis of the economic aspects of CSA technology adoption identified two primary factors that are particularly influential in attracting farmers to adopt these technologies: the perceived benefits and the productivity of the technology. The perception of benefits is largely driven by financial resources available to the farmers, the incentives provided for adopting CSA technologies, and the risk assessment associated with the technology. Financial resources emerged as a crucial driver within this subsystem, influencing the feasibility and attractiveness of adopting new technologies for farmers. The availability of financial resources not only affects the ability of farmers to access and invest in CSA technologies but also shapes their perception of the risks and benefits associated with these technologies.

On the other hand, the productivity of the technology, which is a critical consideration for farmers, is influenced by a combination of factors within the economic subsystem. This includes direct influences such as the efficiency and effectiveness of the technology itself, as well as indirect influences from other variables within the system. The productivity of CSA technologies is a key determinant of their attractiveness, as it directly impacts the potential for increased yield and efficiency in farming practices. The interconnections and dynamics of these economic factors are further detailed in the causal loops analysis. Interestingly, the loops within this economic subsystem are constituted entirely of reinforcing loops. These loops demonstrate the amplifying effects within the system, where positive developments in one area, such as increased financial resources or improved risk assessment, can lead to enhanced perceptions of benefits and greater productivity, thereby further encouraging the adoption of CSA technologies.

The characteristics of the environment of adoption

The role of local context emphasizes the pivotal role of seasonality, risk assessment, and environmental conditions as primary drivers influencing the mitigation of CSA technologies. Moreover, it underscores the crucial impact of the local context within the specific zones where technology implementation takes place. The intricate interaction of these variables gives rise to three reinforcing loops and two balancing loops, as meticulously outlined in Table 1. These loops provide insight into the intricate and dynamic processes involved in effectively mitigating the challenges associated with the adoption and implementation of climate-smart agricultural technologies. This framework sheds light on the multifaceted nature of CSA technology mitigation, underscoring the need for a comprehensive understanding of the local context and infrastructure as key determinants in achieving successful outcomes in CSA initiatives.

The technology characteristics subsystem

The subsystem related to technology characteristics plays a critical role in the overall effectiveness of CSA technology adoption. It encompasses several key components that influence the utility and quality of the technology. At its core, technology performance, its validity, and gender sensitivity are central factors that determine the technology's usefulness. This usefulness, in turn, can be enhanced by factors such as accessibility, durability, and certification of the technology, as illustrated in Figure 2. Additionally, the scalability of the technology and its accessibility and reproducibility also contribute significantly to mitigating challenges associated with CSA technology adoption. The ability to scale the technology, make it accessible to a wider audience, and ensure its reproducibility in various contexts all contribute to its overall effectiveness. Furthermore, the subsystem takes into account the certification of the technology, its reproducibility, cost, and gender sensitivity in defining the quality of the technology package. These factors collectively influence the perceived quality and reliability of the technology, which, in turn, affects its adoption and impact.

When analyzing the feedback loops within this subsystem, the results indicate the presence of seven reinforcing loops and one balancing loop, each with its own implications for the effectiveness and sustainability of CSA technology adoption, as detailed in Table 1. These loops highlight the complex and interconnected nature of technology characteristics and their influence on the broader CSA framework.

Network analysis of the causal loops diagram

The application of systems thinking to analyze the determinants of technology adoption led to the development of a comprehensive CLD. This CLD consisted of 39 determinants that represented the various factors influencing the adoption of technology in the given context. These determinants were interconnected through a network of 130 edges, resulting in an average path length of 3.37. This average path length indicates that, on average, the distance from one determinant to the next in the network was 3.37 steps, highlighting the complexity of the relationships within the system (Table 2). The density of the network, calculated based on the 130 edges used, was 8.77%. This density suggests that the CLD represents a "small world" network, which is characterized by efficient and effective information flow and transition from one stage to the next within the system. It indicates that information and influence can easily propagate through the network, contributing to the interconnectedness of determinants (Table 2).

The degree of connection between determinants within the network varied, with most determinants having a degree in and degree out ranging from 2 to 5. Notably, the training and capacity building determinant had the highest number of cause determinants connected to it, with a total of 8 edges, signifying its significance in influencing other determinants (Table 2). On the other hand, the adaptation determinant had the highest number of effects or influences on other determinants, with 13 cases of degree's in (Table 2).

In terms of network centrality, the adaptation determinant emerged as the most influential within the network, with a betweenness value of 458.8 and a page rank of 0.089. This high betweenness score indicates that adaptation connects various parts of the system and plays a pivotal role in influencing other determinants. The training and capacity building determinant also exhibited a closeness effect within the system, with a closeness value of 0.011 (Table 2). Aside from adaptation and training and capacity building, several other determinants played crucial roles in the network and were identified as key leverage points. These included accessibility, mitigation, certification, technology usefulness, education, technology costs, risk assessments, incentives, and local context (Table 2). Changes in these determinants could potentially result in significant alterations in the interconnectedness of determinants within the system, ultimately impacting the successful adaptation of technology.

Table 2: Network analysis results

NAME	B	C	X	K-in	K-out	K
Accessibility	110.2286	0.008772	0.02	4	6	10
Certification	54.18571	0.009346	0.032844	3	6	9
Cost	84.0119	0.008929	0.021064	3	4	7
Mitigation	132.8167	0.010753	0.027085	7	5	12
Reproducibility	8.309524	0.008264	0.016634	3	3	6
Scalability	5.4	0.010417	0.007505	1	4	5
Tech Usefulness	13.23333	0.008264	0.025668	6	2	8
Adaptation	**458.7119**	0.011111	0.088628	**13**	5	18
Productivity	414.8548	0.010417	0.072849	12	7	19
Tech Validity	13.36905	0.008772	0.036257	4	3	7
Education	147.2833	0.010204	0.035713	3	3	6
Farmer reluctance	199.2143	0.010417	0.022821	2	2	4

Age	88.85714	0.009615	0.021237	1	4	5
Farmer's Knowledge	0		0.009184	1	0	1
Labor	210.95	0.008621	0.058467	6	3	9
Population	0	0.008403	0.009184	1	1	2
Tech Package	0		0.028683	5	0	5
Communication and awareness	8.25	0.006623	0.019556	4	2	6
Health and safety	97.33333	0.00813	0.064092	5	2	7
Monitoring and evaluation	7.75	0.006623	0.017808	3	2	5
Competition	8.066667	0.008475	0.011724	2	4	6
Extension services	20.33333	0.008621	0.010246	2	5	7
Incentive	185.7167	0.010989	0.037485	3	6	9
Durability	4.333333	0.009901	0.005628	1	5	6
Tech Performance	0.333333	0.009346	0.005628	1	5	6
Local context	105.8167	0.009615	0.029571	5	3	8
Technology Change	61.66667	0.009709	0.017873	2	2	4
Environmental Conditions	7.833333	0.007874	0.015204	3	2	5
Risk Assessment	74.16667	0.009259	0.023226	4	4	8
Regulatory Compliance	7.75	0.00641	0.042046	4	1	5
Training & Capacity Building	302.5643	**0.011236**	0.029019	4	**8**	12
Financial Resources	22.2619	0.008547	0.021548	2	4	6
Market access	0.5	0.005587	0.018096	2	1	3
Perceived benefits	72.02857	0.008475	0.028342	4	3	7
Gender	17.85714	0.009259	0.021237	1	2	3
Gender Sensitivity	0	0.007937	0.004671	0	3	3
Income	54.17857	0.006757	0.028899	2	1	3
Infrastructure	0.833333	0.00885	0.009607	1	3	4
Seasonality	0	0.008772	0.004671	0	4	4

2 B = Betweenness, C = Closeness, x = PageRank, K = total Degree, k-in = Degree in, k-out = degree out..

Discussion

In their meta-analysis, [39] [31] examined agricultural technology adoption in the developing world, highlighting the prevalent use of survey data as the primary information source. These surveys typically incorporate a wide range of predictor variables, including socio-economic factors, resource availability, environmental conditions, and various other determinants that can potentially impact the adoption of agricultural technologies, with the majority of analytical methods being of a statistical nature. However, the intricacies of the adoption process become apparent when considering the complex interplay of these predictor variables. It is our assertion that agricultural technology adoption is not a straightforward, linear process. For instance, a farmer's decision to adopt a specific technology may be influenced by various factors, such as their financial status, access to information, and the level of support from agricultural extension services. These factors can interact in nonlinear ways, posing challenges for predicting adoption outcomes solely through statistical models. To tackle this complexity, we advocate for a more comprehensive and systemic approach to the study of agricultural technology adoption. Such an approach entails considering the broader context in which adoption occurs, recognizing the dynamic interactions among various factors, and exploring nonlinear adoption patterns. We construct a CLD that captures the intricacies of CSA technology adoption. This CLD not only visually represents the dynamic system but also serves as a valuable tool for in-depth analysis, improved understanding, and strategic planning in the field of CSA. We examined a wide range of determinants and their interconnections; to provide a holistic understanding of the factors influencing CSA technology adoption and mitigation. This section delves into the key findings, their implications, and potential strategies for enhancing CSA adoption across the continent.

We identified several reinforcing loops within the system, emphasizing the potential for positive feedback mechanisms in CSA technology adoption. For instance, investments in training and capacity building can lead to increased technology adaptation and, in turn, higher productivity. Recognizing these reinforcing loops can help stakeholders identify leverage points for intervention and policy development. It is crucial to note that the success of CSA technology adoption is context-specific, and a one-size-fits-all approach may not be effective. Tailored interventions that consider the unique socio-economic, environmental, and cultural factors of each adoption zone are essential. Collaboration among various stakeholders, including governments, NGOs, research institutions, and local communities, is vital for developing context-specific strategies that promote CSA technology adoption.

We further noticed that a supportive local context significantly influences the success and effectiveness of technology implementation. This underscores the critical importance of tailored strategies that take into account the unique characteristics and challenges present in each adoption zone. To promote the adoption of CSA technologies, policymakers and stakeholders must prioritize investments in infrastructure development and create an enabling environment that fosters CSA technology adoption. In addition to the local context, our analysis highlights the significance of other determinants, such as accessibility, mitigation, certification, technology usefulness, education, technology costs, risk assessments, incentives, and local context. Changes in these determinants can lead to substantial alterations in the interconnections within the system, thus influencing the successful adoption of CSA technology. Therefore, a comprehensive and adaptive approach to technology adoption that considers these determinants is essential for ensuring the sustainable integration of CSA practices in African agriculture.

The analysis also highlights the significance of technology characteristics, including performance, validity, and gender sensitivity [40], in driving technology usefulness. Ensuring that CSA technologies meet the specific needs of local communities, particularly in terms of gender inclusivity, is crucial for their successful adoption. Efforts to enhance technology quality, accessibility, durability, and certification should be prioritized to improve overall technology usefulness. Furthermore, scalability, accessibility, and reproducibility emerged as important factors. CSA technologies that are scalable and easily accessible have a higher likelihood of being adopted and integrated into agricultural systems. Promoting the widespread availability and replicability of CSA solutions can lead to more significant mitigation outcomes.

The examination of the individual subsystems and their intricate web of causal relationships offers a profound and nuanced comprehension of the multifaceted elements that collectively facilitate the successful adoption of CSA technologies. It underscores the imperative need for a holistic approach that extends beyond the technological facets alone. While the technology itself is pivotal, this analysis emphasizes that a comprehensive strategy must encompass regulatory frameworks, educational initiatives, and rigorous evaluation mechanisms to ensure its efficacy. In essence, successful CSA technology adoption is not a unilateral process but an ecosystem where each component, whether it be regulations that incentivize adoption, educational programs that impart knowledge and skills, or evaluation mechanisms that provide feedback and refinement, plays a pivotal role. It is the synergy and harmonious interaction of these components that ultimately lead to the desired outcomes of CSA technology adoption. This comprehensive understanding paves the way for the development of well-rounded and effective strategies that acknowledge and address the interplay of these diverse elements, thereby enhancing the prospects of successful CSA technology adoption in the context of climate resilience and sustainable agriculture

The in-depth exploration of socio-demographic factors within the context of CSA technology adoption yields a profound recognition of the intricate and multifaceted nature of these determinants. This analysis accentuates that the successful adoption of CSA technologies transcends a one-size-fits-all approach and instead calls for a tailored strategy that comprehensively addresses the diverse needs and characteristics of the farmer population. Socio-demographic factors, including but not limited to age, gender, education, and socio-economic status, significantly influence the dynamics of technology adoption. Each demographic group possesses its unique set of challenges, motivations, and barriers. Recognizing these disparities is imperative for devising strategies that resonate with the target audience. Furthermore, the active involvement of technology champions individuals who champion the cause of CSA technology adoption within their communities emerges as a critical catalyst in this process. These champions not only serve as role models but also bridge the gap between technology providers and end-users. They possess an inherent understanding of the local context, cultural nuances, and socio-economic realities, enabling them to effectively communicate the benefits of CSA technologies and address concerns. Their presence fosters trust, instills confidence, and empowers the farming community to embrace these innovations

The process of technology adoption and the spread of diseases, exemplified by the COVID-19 pandemic, reveal striking similarities in their intricate and interconnected dynamics [29]. In both scenarios, a process of diffusion and propagation unfolds, where early adopters or initial cases wield influence over others through diverse channels. This influence is amplified by network effects, where a critical mass of adoption or infection can trigger positive feedback loops, accelerating the overall process. Yet, both contexts also feature elements of resistance and immunity that necessitate targeted strategies for surmounting barriers. Behavioral change serves as a central pivot in both cases, as individuals and communities must adapt their actions, underlining the importance of understanding the motivations and obstacles that drive such changes.

In managing these complex systems, governments and policymakers wield significant influence through the implementation of regulations, incentives, and resource allocation. Particularly, incentives play a pivotal role in promoting technology adoption. These incentives, whether they take the form of financial rewards, recognition-based programs, or improvements in working conditions, act as powerful motivators, encouraging individuals and organizations to prioritize and invest in adopting CSA technology. Furthermore, there is a notable parallel in the mathematical foundations shared by epidemiological models for disease and adoption models for technology. These commonalities facilitate forecasting and intervention planning, offering valuable insights into how to navigate and manage complex systems effectively. Recognizing these parallels underscores the importance of multidisciplinary approaches that draw from various fields to address the challenges posed by both disease outbreaks and the adoption of CSA technology, ultimately contributing to more informed and holistic strategies for managing complex systems

CRediT authorship contribution statement

Ghislain T. Tepa-Yotto: Conceptualization, Investigation, Methodology, Funding acquisition, Writing – original draft. Bonoukpoé M. Sokame: Investigation, Methodology, Writing – review & editing. Fidèle T. Moutouama: Investigation, Methodology, Writing – review & editing. Cyriaque Agboton: Investigation, Methodology, Writing – review & editing. Jeannette K. Winsou: Investigation, Methodology, Writing – review & editing. Henri E.Z. Tonnang: Conceptualization, Methodology, Supervision, Writing – review & editing.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The funders had no role in the design of the study; in the assemblage and interpretation of data; in the writing of the paper, or in the decision to publish the results.

Data, materials, and software availability

Code and data have been deposited in https://dmmg.icipe.org/. All other data and links are included in the manuscript

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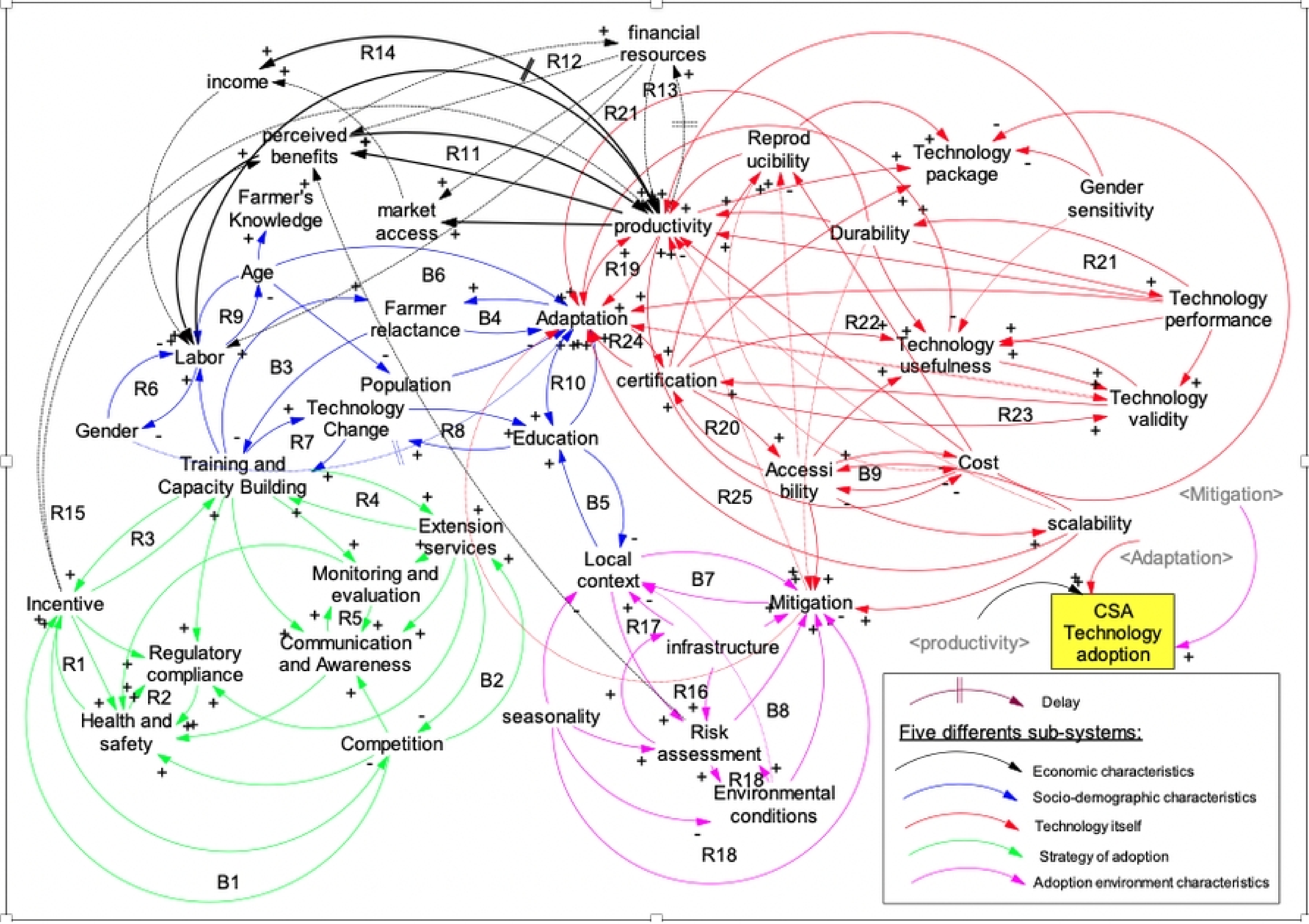
Figure


financial resources
income
R14
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R13
R21
perceived benefits
R11
Farmer's Knowledge
market access
productivity
Reprod ucibility
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R21
Technology performance
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Farmer relactance
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Technology usefulness
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R10
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R7
R8
Education
R20
Accessi bility
B9
Cost
Training and Capacity Building
R25
<Mitigation>
R4
B5
scalability
R15
Extension services
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R3
Monitoring and evaluation
Local context
B7
Incentive
Mitigation
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R5
R17
Regulatory compliance
Communication and Awareness
infrastructure
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R1
R2
B2
R16
Health and safety
seasonality
B8
Risk assessment
Competition
R18
Environmental conditions
R18
B1
Delay
Five differents sub-systems:
Economic characteristics
Socio-demographic characteristics
Technology itself
Strategy of adoption
Adoption environment characteristics

Figure