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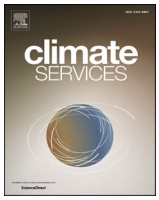

Constructing A Climate-Smart readiness index for smallholder farmers: The case of prioritized bundles of climate information services and climate smart agriculture in Ghana

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HIGHLIGHTS

- Climate Smart Agriculture (CSA) technology and Climate Information Services (CIS) prioritization and bundling are perquisite technology update readiness.
- Criteria for CIS-CSA prioritization in includes Climate Smart Agriculture (CSA) achievement, addressing Gender, Youth and Social Inclusion (GSI), Enabling Environment (EE), One-Health Achievement (OHA), End-User Friendliness (EUF) and ultimately to construct a Climate Smart Readiness Index (CSRI)
- Climate Smart Agriculture (CSA) technologies and Climate Information Services (CIS) bundling are more impactful when integrated.
- The CS and EUF had a significant intra-rater agreement among farmers while EE had a substantial intra-rater agreement among advisors.
- One-Health Achievement (OHA) is a fundamental factor in determining Climate Smart Readiness Index (CSRI) for farmers whereas Enabling Environment (EE) was considered more important by advisors.
- Based on this, Climate Readiness Index is useful for bundling purposes and not for prioritization.
- This is an evidence for farmer preparedness in the context of resilience, productivity, adaptation, and mitigation
- Policy makers and agricultural practioners will best understand and have prior knowledge about the priority setting for effective bundles and this study will help them to bundle during policy and programme formulation.

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ABSTRACT

Issues around bundling of climate smart agriculture (CSA) and climate information services (CIS) have been kept relatively distinct whereas in reality, they are more impactful when integrated. Using the case of the Accelerating Impacts of CGIAR Climate Change Research in Africa (AICCRA) Project that emphasizes bundling as a critical component of research in development, six regions of Ghana were purposively selected based on the identified value chain crops for implementation. 120 respondents including practicing farmers and advisors as reference, rated contributions of 21 innovations to 25 climate smartness indicators. These include gender, youth and social

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inclusion (GSI), enabling environment (EE), ability to enhance soil, water, crop and animal health (One-Health Achievement) (OHA), end-user friendliness (EUF) and climate smart agriculture (CS) for prioritization, bundling and ultimately to construct a Climate Smart Readiness Index (CSRI). There was a high level of concordance between the ratings of farmers and advisors on the Climate Smartness; moderate concordance on OHA and a lower concordance on GSI. The CS and EUF had a significant and same agreement among farmers while EE had a substantial same agreement among advisors. These elements (CS, GSI, OHA, EUF, EE) formed an integral part of the CSRI construct confirmed by the Fornell-Larcker and the Heterotrait-Monotrait criteria. While OHA was the fundamental factor in determining CSRI for farmers, EE was considered more important by the advisors. CSRI informs policy makers and agricultural practitioners on appropriate bundling of CSA and CIS practices to generate evidence for farmer preparedness in the context of resilience, productivity, adaptation, and mitigation.

Practical implications

Climate-smart readiness index is a potential realization based on the contributions of each Climate Smart Agricultural technology (CSA) and Climate Information Services (CIS) pillar from farmers and agricultural extension experience. Prioritization and bundling of CSA-CIS are part of the decisions based on a set of criteria to inform choice and uptake of technologies. These decisions are critical to addressing the gender and youth involvement in various agricultural commodity value chains in Ghana.

Agricultural extension agents serve as advisors and hence validate farmers choice of CSA-CIS bundles on seasonal basis. CSA addresses efficiency in resource allocation and use backed by appropriate CIS access. CSA-CIS intersect at the common need of enhancing farmers' resilience in the context of climate change. Bundling readiness supports farmers preparedness to derive satisfaction from the appropriate combination of CSA-CIS and explains the behavioral and socio-economic factors underpinning climate-smart readiness. Farmers and extension officers (experts in agricultural), found fundamental differences in the level of concordance between their categories of actors.

Climate smartness, Gender and Social Inclusion (GSI) and moderate concordance on One-Health Achievement (OHA), End-User Friendliness (EUF) are critical considerations for both farmers and agricultural extension agents while Enabling Environment (EE) is an added consideration to prioritization of CSA-CIS bundles in Ghana.

Farmers consider the One Health Achievement (OHA) as a fundamental factor in determining CSRI whereas the Enabling Environment (EE) is considered by agricultural extension agents. Farmers are concern about food safety and increased yield due to the high level of prioritization of vine technology, and pest and disease tolerance while advisors have broader concerns.

Data availability

Data will be made available on request.

1. Introduction

Smallholder farmers' readiness to the eventualities of climate change is a latently measured construct that is scarce in mainstream literature, but fast gaining salience in Participatory Action Research (PARs) domains (Arbuckle and Lasley, 2013; Epule et al., 2021; Preston et al., 2011). It is consequential for policy design as well as designing responsive and well-targeted project interventions. It defines the speed of adjustments or resilience recovery pathways among smallholder farmers to the ever-changing farming environment. Human induced temperature extremes, wet and drought conditions are projected to reconfigure terrestrial ecosystem structure and species range in western Africa, thereby adversely affecting food security, livelihoods, infectious diseases, and economic output especially for the low income groups (IPCC, 2022). Evaluating climate readiness is therefore deemed urgent (Nyamekye et al., 2021) as timely informed adjustments in readiness would minimize climate-change vulnerabilities (Arbuckle et al., 2013; Chemura et al., 2020; Djido et al., 2021; Guido et al., 2020). The problem of declining productivities attributable to over-dependance on rain-fed agriculture and declining optimal suitability of seeds from farmer-saved crop varieties can partially be solved through bundling Climate Information Services (CIS) with Climate Smart Agriculture (CSA) (Adzawla et al., 2019; Chemura et al., 2020). Bundling is a novel area for research positing that CIS and CSA are complimentary and in practice, proposed as a means of ensuring and supporting farmer readiness to the consequences of climate change. Therefore, bundled climate smart agricultural practices and climate information services, offered through different research for development projects may serve as conduit for reducing or even reversing the consequences of climate risks within farming communities and reveal the climate smart readiness among smallholder farmers.

Climate smart agricultural practices and climate-information services are already being implemented to enhance farmer's resilience through Participatory Action Research (PAR) in Ghana under the former CGIAR Research Program on Climate Change, Agriculture, and Food Security (CCAFS) and the Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) project (c; Djido et al., 2021; Simelton et al., 2018; Tesfaye et al., 2021). AICCRA project puts much effort into bundling CIS and CSA and calls for gender, youth and social inclusion into these practices (Damba et al., 2021). It is worth noting that youths and women are more involved in efficient uptake and utilization of CSA-CIS practices due to their inaccessibility to critical resources (Nchanji et al., 2021a; Nchanji et al., 2021b). Targeted interventions of CSA-CIS technologies may be corresponding to the research calls that advocate for bundling of the two concepts (CIS and CSA) as they are indistinct (Djido et al., 2021; Simelton et al., 2018). Further calls for bundling CIS and CSA can be found in Prager et al. (2021) who advocate for agriculture products and practices that support sustainable scaling in the delivery of the same; and the business models that can support the implementation of CIS and CSA in a manner that maximize benefits for both farmers and the private sector stakeholders. CSA practices are complementary in nature with CIS and farmers combine multiple strategies to adapt to climate change (Zakaria et al., 2020). Despite efforts to mitigate climate risk vulnerabilities through programmes such as CCAFS and AICCRA, it is not clear how they can trigger climate-smart readiness.

This paper develops the concept of bundled CSA and CIS practices/technologies and goes further to develop latent construct that evaluates if farmers or farming systems are climate-smart ready. Theoretically, the CIS and CSA practices/technologies that are complementary both in nature and practice, when bundled as a package and given to farmers (who may adopt the technologies) should offer farmers better preparation for climate change, reduce vulnerabilities to climate-triggered agricultural risks and improve resilience. However, *ex ant* empirical evidence seem mute on how such climate-smart readiness is reflected through bundled practices and how it can trigger pro-environmental behaviors that include water use efficiencies, adoption of climate-resilient crop varieties and value chains, reduce carbon footprints, change perceptions and behaviors

on climate change, gender and social inclusion and one-health achievement (Arbuckle et al., 2013; Wiid and Ziervogel, 2012).

This study overcomes limitations and contributes to climate change literature in the following manner. First, bundled CIS and CSA practices have few frameworks that can guide practitioners (Damba et al., 2021; Shrader et al., 2020; Tesfaye et al., 2021). Second, there is incoherence in attempts to define groups of variables that can be used to describe climate-smart readiness in literature. This study uses farmer and extension officer ratings (experts in agricultural advice) and proposes main tenets of climate-smart readiness as gender and social inclusion, one-health achievement, enabling environment, end-user friendliness and climate smart agriculture indicators. Third, through literature review, we found attempts to define climate smart readiness but realized a fundamental flaw in theoretical grounding, conceptualization and econometric approaches to construct indices (Epule et al., 2021; Ford and King, 2015; Khan and Amelie, 2015; Nhamo, 2013). This study uses the recommended approaches for constructing composite economic indicators using structural equation modelling, specifically, the Partial Least Squares (PLS) to develop a readiness index (OECD, 2008; Vyas and Kumaranayake, 2006). Fourth, we contribute to action research by using current project portfolios (CCAFS and AICCRA) in Ghana – where more than 10 years of long-run practical farmer-targeted CSA and CIS interventions have been made.

Related studies

Bundled CSA and CIS practices.

The concept of CSA was launched by the Food and Agricultural Organization of the United Nations (FAO) in 2009 to draw attention of practitioners on how interlinked food security and climate change are (FAO, 2018). Recently, it has sprawled into a mainstream conceptual framework that advocates for: i) increased agricultural resource use efficiency and ii.) enhanced resilience of agricultural systems and farmers (ibid). On the other hand, CIS has evolved over the last 30 years to address three critical issues; namely, access to information, knowledge exchange, and social networks in agriculture through technology-driven data on weather and climate change information used for climate advisory practices aimed at enhancing resilience of farmers (Economic Commission for Africa, 2021; Guido et al., 2020). Critical analysis of the two concepts reveal their intersectionality and complementarity, rather than being separable disjointed actions as seen in most literature (Bayala et al., 2021; Partey et al., 2018; Simelton et al., 2018). While CSA addresses efficiency in resource use, CIS addresses access to critical technology to exploit such resources more efficiently. The concepts intersect at the common need of enhancing farmers' resilience in the context of climate change. Thus, there is a need to bundle (offer CIS and CSA as one joint product) these practices as farmers may benefit more.

Bundling CIS with CSA is a relatively novel area for research and there exist few, but growing frameworks aimed at informing the practitioners on how this can be done. The framework developed by Tesfaye et al. (2021) used panel data endogenous switching regression model to provide microeconomic evidence of the welfare effects of conservation agriculture (CA), and climate-smart agricultural practices. Their findings indicated that bundling these practices would empower farmers to make appropriate decisions, minimize 'technology failure', provide pathway for technology adoption and enhance resilience at the household level among others. Shrader et al. (2020) framework also showed that digital climate smart practices such as bundled CIS and CSA may offer farmers enhanced climate change responses. The framework gives practical evidence on where such practices are already taking place. Another attempt by Damba et al. (2021), given the complementarity of CSA-CIS practices, included in the AICCRA project 5 bundles composed of improved and drought tolerant seeds, water management (small scale irrigation), seasonal calendars and soil fertility improvement products but this approach failed to provide weight on scores by various stakeholders.

In the thin existing literature, we found studies that report results from bundling CSA-CIS practices. The first one by Mariam et al. (2019) provided drought tolerant maize seeds as CSA option and bundled it with weather-based index insurance and diversified options for livestock for farmers in Southern Africa. They found private sector involvement, galvanizing institutional leadership, financial incentives and innovative value chains to be the drivers of CSA-CIS bundled practices adoption. Afari-Kwarteng and Adedeji (2019) provide three instances through various projects under the Centre for Agricultural and Rural Cooperation (CTA) in which bundled practices ranging from microcredit provision for good agricultural practices adoption, SMS-based rural extension service provision and livestock insurance as a CSA service with blended weather information system led to reduced banana rejection by 10 percent, increased use of weather-based insurance and increased hay production and cheaper fodder for animals. In Southern Malawi, Alexandratos and Bruinsma (2012) found integration of CSA practices into conventional maize-legume systems with increased climate information as profitable to farmers but short-run/upfront seemed high compared to conventional practices. In India, Farahani et al. (2010) found that bundling agronomic practices with CIS promoted better semi-arid farming systems but recommended inter-disciplinary and gender-sensitive approaches as important attributes of successful CSA-CIS bundled practices. The assessment compared PLS model which provides a more stable output than the OLS regression model especially for small sample size. In Zimbabwe, Mujeyi et al. (2020) also applied the Principal Component Analysis (PCA) to identify the combination of CSA technologies and found bundled labor-saving CSA technologies, adoption of minimum tillage, manure among others bundled with access to weather forecasts and capacity building through trainings increased the likelihood of adopting CSA-CIS bundles.

Further assessment of the above studies does not provide clear empirical evidence on whether bundling CSA-CIS practices prepares farmers for climate change eventualities. Nonetheless, they inform us on the conspicuous potential of the bundled practices to transforming technology-driven climate change adaptation and resilience for smallholder farmers. It is of interest to also view attempts to define climate-smart readiness and studies that use such criteria.

1.1. The concept of climate-smart readiness index

Climate-smart readiness index is conceptualized as a potential realization based on the contributions of each CSA and CIS pillar from the farmer and advisors' ratings of value chain crops and technologies promoted by the CCAFS and AICCRA in Ghana as shown on Fig. 1 below. It follows the long-standing cocepts of development economics, especially 'indices' that measure latent constructs such as resilience, human development index, gender inclusivity index among others. Just like non-existence of mono-dimensional indicator of factors such as resilience as demonstrated by Levine (2014), a climate-readiness indicator is a composite index that exhibits non-equilibria dynamics and constructed through procedures proposed in McGuckin et al. (2001).

Previous literature, attempts to define climate readiness as a latent construct or proxy through existing variables (Epule et al., 2021; Ford and King, 2015; Khan and Amelie, 2015; Nhamo, 2013). First, Epule et al. (2021) attempted an econometric analysis of linear interpolation to develop a climate readiness index that fundamentally averaged ratings of indicators, a potential fundamental methodological flaw in producing indices (OECD, 2008). Ford and King (2015) defined adaptation readiness qualitatively (lacks reproducibility) while Khan and Amelie (2015) developed adaptation readiness in Seychelles to identify governance frameworks that influence climate change readiness. The Notre Dame Global Adaptation Index (ND-GAIN) developed by Chen et al. (2015) used climate vulnerability data of 74 variables to form 45 core indicators to construct the index. The work was not contextualized in the realm of smallholder farmers and may not be used to generalize the indicators of climate readiness for farmers in Sub-Sahara Africa.

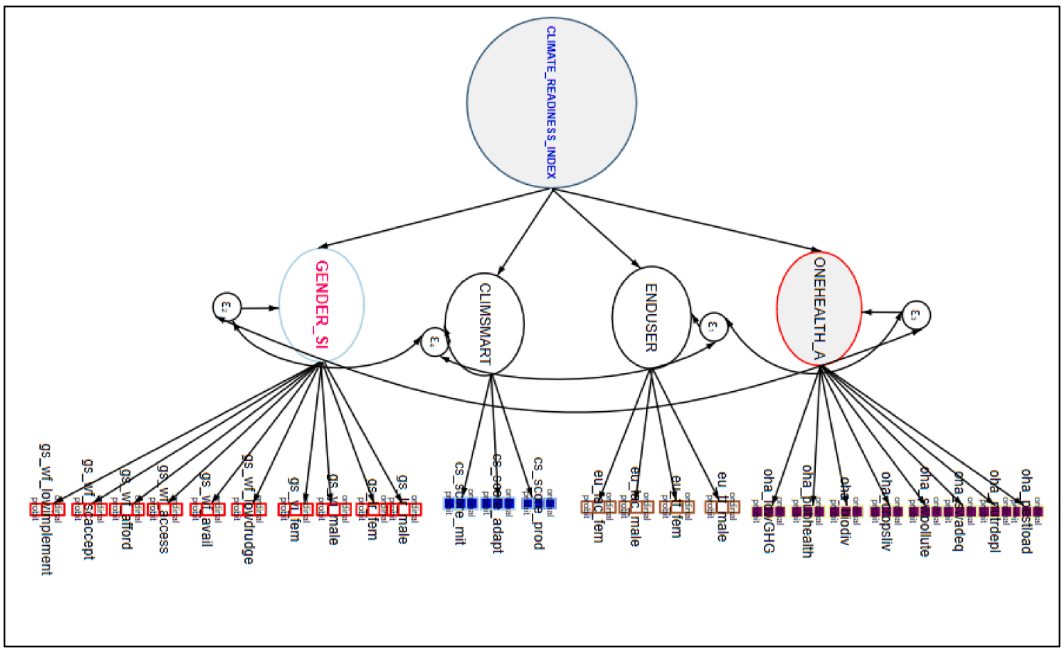

Fig. 1. Conceptual framework for the climate smart readiness index.

From these sampled works, it is also evident that some arguable fundamental flaws exist in conceptualization, methodological approaches, variable construction, econometric estimation methods and general lack of technical understanding of climate-related indices as latent constructs that should follow the procedures of composite indices construction (OECD, 2008). This observation is guided by *meta*-analyses and recommendations from various authors on well-evidenced methods and guidelines on construction of composite indicators (McGuckin et al., 2001; OECD, 2008; Preston et al., 2011). To overcome the above-mentioned limitations, this study first developed theoretical underpinning of the latent construct and envisions the bundled practices as pathways through which the latent construct may be assessed.

Conceptually, the readiness index is modeled as an exogenous latent variable based on a reflective measurement model. The directions of the arrows point away from construct; meaning that the ordinal indicators measuring the bundled CSA-CIS practices offered to smallholder farmers are reflective of climate-smart readiness. The indicators may be considered interchangeable (as defined in reflective models); thus, the removal or addition of one of the pillars/items do not affect the nature of underlying latent construct, i.e., climate-smart readiness. Any changes in climate smart readiness are reflected in changes in observed ordinal indicators (more precisely, the covariation) with an error term. The indicators are *congeneric* because none loads on more than one latent construct selected *a priori*; and such relationships should be considered definitional rather than causal (FAO, 2016). The conceptual framework can be tied with our utility maximization and VBN theory (discussed below) in that if the farmers are climate smart ready, then they will most likely adopt the CSA-CIS bundles measured by the 4 indicators (described shortly).

The ratings of the technological contributions to the three CSA pillars of productivity, adaptation and mitigation were first assessed as they illustrate the potential for the practice to generate positive effects for the farming system. Adaptation and mitigation are the main pillars of CSA as identified in literature (Epule et al., 2021; Ford and King, 2015; Guido et al., 2020; Wiid and Ziervogel, 2012). Secondly, gender and social inclusion with its 4 indicators on labor requirement, youth involvement, lowered costs and women's friendliness of CSA-CIS bundled practices are evaluated. Gender and social issues have been deliberated to be central part of climate change adaptation and information technology access especially for women and youths in Sub-Sahara Africa (Muricho et al., 2021; Mwongera et al., 2020; Nchanji, 2021). Specifically, ratings/evaluation of technological women friendliness in terms of lowering associated drudgery, improve accessibility and affordability of practices, technologies that are socio-culturally appropriate, and those practices/technologies that lower requirement for technical skills for their implementation are included. The study also includes 6 indicators of One-Health Achievement (OHA) assessed through ability of the technology to reduce pest load, increase soil–water adequacy, lower GHG emissions, and whether it addresses nutrient depletion, soil–water pollution, and preserved biodiversity. OHA is emerging as an interesting area in climate change studies because it is a holistic approach that considers the connections between the environment, animals and plants and how they impact human health (Ruscio et al., 2015; Zinsstag et al., 2018). The study also includes 4 indicators for end user acceptance and enabling environment such as access to local institutions, market linkages, technical feasibility, and farmers' investment capacity to adopt the practices. By assessing these indicators of bundled CSA-CIS practices, the study aims at developing a climate-smart readiness index.

2. Materials and methods

2.1. Theoretical framework

Smallholder farmers would theoretically want to maximize profit (net returns) and minimize cost on a bundle of CSA-CIS practices offered by practitioners. This is because, if these bundles and climate action policies promote human happiness in the end, they would be morally right and farmers would maximize utility derived from them in a diminishing marginal utility fashion as explained in Betham (1823) and Mill (1863). The benefits derived from bundled practices would be ordinal implying that satisfaction from the use of CSA-CIS would be ranked due to their competitive nature for an alternative technology bundle or combinations of such. In theory, two conditions guide one's decision on choices among the alternative CSA-CIS bundles – transitivity and indifference relations (Aleskerov et al., 2007). The transitivity condition requires that if a rational farmer prefers bundle x to y and y to z, then s/he must prefer x to z. Here, the farmer will choose bundle x over the others; x is known as the utility maximizing choice. Again, an

Table 1
Study area of bundling of climate smart agriculture (CSA) and climate information services (CIS) in Ghana.

Region	Average Rainfall/ Temperature	Districts/ Municipalities/ Metropolis	Towns/Communities	Commodity
Central	86.76 mm/ 27.62 °C	Cape Coast Metropolis	Mempeasem, Afutu Dehyia	Sweet potato
		Elmina Municipality	Dompoase, Anyinase	Sweet potato
Bono East	1050 mm/ 21 °C	Kintampo North	Adomano, Bawakura	Maize, cowpea, yam
		Kintampo South	Adiembra, Agyegyemakumu	Maize, cowpea, yam
		Techiman North	Offuman, Tano Boase	
Northern	49.53 mm/ 35.34 °C	Tolon	Nyankpala, Yizeigu, Woribogo,	Maize, Cowpea, yam, Sweet potato
Upper East	44.5 mm/ 31.47 °C	Navrongo Municipal	Tampola	Tomato
		Bongo District	Yindongo	Tomato
Upper West	107.5 mm/ 40 °C	Lawra District	Bompare, Dazuuri	Maize, Cowpea
		Jirapa District	Doggoh	Maize, Cowpea

indifference relation exists in a respondents' choice if s/he neither prefers bundle x to y nor y to z. In the latter instance, the farmer considers all three choices as belonging to the same indifference class – neither alternative (x, y, or z) provides superior utility over the others.

Thus, for each CSA-CIS bundled service j for farmer i and an alternative bundled service k:

$$U_{ij} = \beta_j + \varepsilon_j \; and \; U_{ik} = \beta_k + \varepsilon_k) \tag{1.1}$$

Where: U_j and U_k are the ordinal utilities of alternative CSA and CIS bundled practices, X_i is an ordered vector embodying socio-econometric and behavioral covariates, β's are the parameters estimates and ε's are the error terms. The maximized utility based on competitive nature of the associated bundles j and k given the farmer characteristics X_i, may be realized when utility from j is greater than utility from bundle k:

$$U_{ij}(\beta_j X_j + \varepsilon_j) > U_{ik}(\beta_k X_k + \varepsilon_k) \tag{1.2}$$

Assuming household resources are pooled, efficient allocation is feasible, and the organization of production is efficient, farmer i's first ranked CSA-CIS bundled alternative is thought of as maximizing ordinal utility.

In addition, farmers' behaviors, beliefs, attitudes and such intrinsic values (not captured in classical utility maximization theory) would be embodied in the value-belief- norm (VBN) theory of environmentalism (Oreg and Katz-Gerro, 2006). The VBN theory extends Ajzen's (1991) notion that beliefs antecede behavioral intentions, and these in turn antecede the actual behavior. Climate change beliefs and perceptions antecede behavioral norms which in turn antecede actual pro-environmental behaviors such as water use efficiency, adopting climate-resilient varieties, adopting user friendly farming technologies among others. Thus, CSA-CIS buddled practices follow a causal chain as it demonstrates that environmental beliefs that result in resilient farming societies are anteceded by personal values (Bratt et al., 2015; Oreg and Katz-Gerro, 2006). Therefore, climate smart readiness is a utilitarian– anthropocentric, and ecological problem underpinned and set up in a multifactorial dimension that combine the classical CSA side pillars (productivity, adaptation, and mitigation), gender and social inclusion, one-health achievement and CIS pillars such as technological end-user friendliness and technology-driven enabling environment for smallholder farmers.

3. Methodology

3.1. Study area

The study was undertaken in the six AICCRA Regions of Ghana comprising the Greater Accra, Central, Bono, Northern, Upper West, and Upper East. In each region, the districts were purposively selected based on the identified value chain crop for implementation. Specifically, the Weija District was selected in the Greater Accra Region; Cape Coast Metro and Elmina Municipality were selected in the Central Region; Kintampo North, Kintampo South, and Techiman North were selected in the Bono Region; the Upper West Region was represented by the Lawra and Jirapa Districts while the Navrongo Municipal and Bongo District in the Upper East Region. In each selected Metropolitan, Municipal, and District Assembly (MMDA), at least one community was selected for the field survey; these details are presented in Table 1. These locations were selected based on the extreme effects and impacts of climate change on smallholder farmers' activities. These areas have received climate change interventions over the last decade and therefore, farmers and agricultural experts are in position to prioritize CSA-CIS technologies and practices based on a set of indicators.

Following on past agricultural technologies implemented in various parts of Ghana including the AICCRA-Ghana, communities and respondents were selected along the maize, cowpea, roots and tubers (yam and sweet potato), and the vegetable (tomato and pepper) value chains. These practices were identified by farmers, and advisors in the various districts and regions consisting of the Northern, Upper West, Upper East, Bono East, Greater Accra and Central. In all, a total of 22 existing CSA-CIS practices were identified and compiled along commodity value chains. These 22 CSA-CIS practices were sub-categorized based on geographical and value chains and subjected to four broad themes which include: i. Climate Smartness, ii. Gender and social inclusion, iii. Achieving one-health and iv. Enabling environment for easier uptake and usage. These broad thematic areas were unpacked into: i. climate smartness (productivity, adaption and mitigation); ii. Gender and Social Inclusion (low labor requirements, youth involvement, lower associated cost, women friendliness i.e. Lower drudgery, availability, accessibility, affordability, socio-cultural appropriateness, and lower implementation requirements); One Health Achievement (reduced pest load, addresses nutrient depletion, address soil–water adequacy, addresses soil–water pollution, preserves biodiversity, lowers GHG emissions); and Enabling Environment (access to local institutions, market linkages, technical feasibility, and farmers investment capacity). These criteria were identified as a prioritization strategy adapted from series of works, projects and indicators from projects that are found to be critical and sensitive to gender and youth sensitivity.[1]

3.2. Sampling and data collection procedure

Purposive sampling was used to select the districts, communities and respondents consisting of farmers, researchers, and advisors in the various communities. These respondents were further selected based on their roles, existing knowledge and practices in the various commodity value chains consisting of maize, cowpea, yam, sweet potato and tomato value chains. In all, a total of 71 respondents were selected based on their role and expertise in the various community value chains from Greater Accra, Central, Bono, Northern, Upper West and Upper East, respectively.

[1] https://ccafs.cgiar.org/resources/tools/climate-smart-agriculture-rapid-appraisal-csa-ra-prioritization-tool#.VNyxJfmG_94.

3.3. Empirical strategy

In this study, we used the non-parametric Partial Least Squares Structural Equation Modelling (PLS-SEM) technique to estimate the climate readiness indicator; and as an alternative to the Maximum Likelihood Structural Equation Modelling (ML-SEM). This is because of its popularity in reflective and formative measures as evidenced in a review of 196 of the 239 studies, where 82 percent of the studies used PLS-SEM instead of ML-SEM (Sarstedt et al., 2022). Besides, its relaxation in the assumptions on data distribution and acceptance of smaller sample sizes (Hair et al., 2017); its outperformance of ML-SEM when there is high inter-correlation among manifest variables, and its better performance when small disturbance variance exist in data (Dolce and Lauro, 2015) are other reasons for considering its use in our study. Among the variance-based SEM techniques such as regression on the principal components and the generalized structured component analysis, PLS-SEM is the "most fully developed" and considered a "silver bullet" by most practitioners, thus used in this study (Hair et al., 2017).

In essence, we fit:

$$\eta = B\eta + \Gamma\xi \tag{1.4}$$

Where vector $\eta(m \times 1)$ is a container of all the dependent variables, $\eta' = [y', \pi']$ where y is a vector of all the reflective indicators of the endogenous latent constructs (Climate Smartness Score (CS), Gender and Social Inclusion (GSI), One-Health Achievement (OHA), End-User Friendliness (EUF), Enabling Environment (EE) represented by π in the model. The vector $\xi = (n \times 1)$ represents the independent variables, $\xi' = [x', \tau', \zeta, \varepsilon']$ contains the manifest variables x, exogenous/endogenous latent variables τ, the disturbance terms ζ, and the associated measurement errors ε. $B(m \times m)$ and $\Gamma(m \times m)$ capture the coefficients of the effects of the independent variables on the defined dependent variables.

We strongly recommend that this study be considered as an exploratory one because the aim is to search for patterns in the data, test and substantiate the hypotheses of the *a priori* determined latent factors and their assigned indicators with the assumption that there does not exist or only little prior knowledge about how to estimate climate-smart readiness indicator exist. Thus, we fit a reflective model where the indicators would assumptively be considered as imperfectly reflecting the underlying construct as discussed in MacKenzie et al. (2011). The reflective measurement model (modified for eqn (1.4) and estimated through PLS) is therefore presented as:

$$\eta = B\gamma + \varepsilon \tag{1.5}$$

Where is a vector indicator, B is the matrix of factor loadings and ε is the disturbance term for indicators in the model.

A two-stage approach was used, whereby the lower-order constructs (LOCs) composed of climate smartness scores and end-user friendliness were first estimated followed by high-order constructs (HOCs) that included the latent climate smart readiness index, gender and social inclusion and one-health achievement components. The approach was chosen to reduce the number of path model relationships and encourage parsimony; but also, to overcome the bandwidth-fidelity dilemma (Polites et al., 2012). The first two constructs are put in LOCs based on our belief and the arguments/clarifications of Chin and Marcoulides (1998) that LOCs are unique and selectively measured constructs that seldom share a common cause. Instead, they form a general concept that entirely mediates the impact on subsequent endogenous variables.

We compare the results from the traditional PLS with those of consistent PLS-SEM and apply the bias-corrected and accelerated (BCa) bootstrapping with 5,000 bootstrap samples at the 95 percent bootstrap percentile confidence intervals. The latter method corrects the estimates of the constructs measured reflectively by estimating a novel reliability coefficient ρ_A (Dijkstra and Henseler, 2015). Traditional PLS has consistency problems when estimating common factor models but PLSc (c-consistent) seldom produce an unwarranted number of false positives even when data is not normally distributed.

4. Results and discussions

4.1. Concordance in perceptions between farmers and advisors

Table 2 shows the results of the level of agreements or disagreements in rankings by farmers and advisors. As earlier discussed, it would be expected that advisor's rankings of the CSA and CIS practices and value chains would be more informed by their expertise while the farmer's rankings would be dependent on their experience with the CSA and CIS bundles that were provided to them through the projects.

Overall, there was a highly significant degree of concordance between ratings of farmers and advisors on the Climate Smartness (CS) score indicators (0.75). This is classified as a substantial agreement among raters (Viera and Garrett, 2005). However, intra-rater concordance among the farmers (0.46; $p \leq 0.1$) was moderate compared to the substantial agreement among the advisors (0.75; $p \leq 0.001$). Farmers were more likely to rank productivity item high with a mean and standard deviation of 3.58 and 0.89, respectively as shown on Table 3. This means the CSA and CIS practices were of medium to high importance to them. The advisors ranked productivity highest with a mean and standard deviation of 2.74 and 1.94, respectively. However, this was a low importance to moderate importance ranking of the practices and value chains associated with productivity. Therefore, the concordance seemed to have occurred on the moderate importance of the practices and the value chains.

The results for Gender and Social Inclusion (GSI) indicator showed that the null hypothesis would be rejected in favor of alternative hypothesis – meaning there was concordance in the rankings of the items. The low value of 0.22 ($p \leq 0.05$) means there was fair agreement according to the classification by Viera and Garrett 92005). Farmers seemed to highly rank women friendly and socially acceptable CSA-CIS bundled practices with a mean and standard deviation of 3.65 and 1.06, respectively (Table 2). On the contrary, the advisors ranked the extent of youth involvement in the activity by males as the most important GSI indicator with a mean and standard deviation of 3.85 (0.94) respectively. Women friendliness in reducing drudgery was the lowest rated among farmers with a mean and standard deviation of 2.72 and 1.03 respectively, while women friendliness practices that were socially acceptable to women in their settings was the lowest rated among the advisors with a mean of 1.67 and standard deviation of 1.21.

The highly significant One-Health Achievement (OHA) value of 0.49 shows a moderate concordance (see, Viera & Garrett, 2005) between the farmers and the advisors (Table 2). Intra-rater agreement among the advisors was 0.5 (moderate) while that of farmers was 0.36 (fair). As shown on Table 2, among the farmers, the highly ranked items for OHA were whether the CSA practice reduced pest load (mean 3.14 and SD 0.97) and whether the practice had public health implications by contributing to the lowering incidences of diseases to humans (mean

Table 2
Kendall's Coefficient of Concordance of variable groupings among farmer and advisors for bundling of climate smart agriculture (CSA) and climate information services (CIS) in Ghana.

Indicator	Kendall's Coefficient of Concordance		
	Overall	Farmers	Advisors
Climate Smart Score (CS)	0.75***	0.46*	0.75***
Gender and Social Inclusion (GSI)	0.22***	0.23**	0.22**
One-Health Achievement (OHA)	0.49***	0.36***	0.50***
End-User Friendliness (EUF)	0.40***	0.40***	–
Enabling Environment (EE)	0.69***	–	0.69***

Note: ***, **, * statistically significant at 1%, 5% and 10% level respectively.

Table 3
Bundling of Climate Smart Agriculture (CSA) and Climate Information Services (CIS) in Ghana.

Latent constructs and indicators	Farmers						Advisors					
	mean (SD)	min–max	avg. inter-item corr.	alpha	FL	OL	Mean (SD)	min–max	avg. inter-item corr.	alpha	FL	OL
a. **Climate Smartness Scores (CS)**												
Score on productivity	**3.58 (0.89)**	[1–5]	0.49	0.65	0.6	0.95	**2.74 (1.94)**	[1–5]	0.86	0.93	0.89	0.97
Score on adaptation	3.25 (0.95)	[1–5]	0.24	0.39	0.81	0.31	2.24 (1.48)	[1–5]	0.88	0.94	0.82	0.96
Score on mitigation	3.47 (1.02)	[1–5]	0.25	0.4	0.81	0.52	2.24 (1.61)	[1–5]	0.92	0.96	0.85	0.95
b. **Gender and Social Inclusion (GSI)**												
Labor requirements: level of effort to implement activity by males	2.77 (1.13)	[1–5]	0.14	0.6	0.51	0.37						
Labor requirements: level of effort to implement activity by females	3.16 (1.07)	[1–5]	0.13	0.58	0.59	0.48						
Labor requirements: general level of effort to implement activity							3.48 (1.44)	[1–5]	0.19	0.66	0.64	0.4
Activity has low associated cost							3.26 (1.47)	[1–5]	0.17	0.62	0.77	0.58
Extent of youth involvement in the activity: males	3.53 (0.95)	[1–5]	0.12	0.54	0.7	0.62	**3.85 (0.94)**	[2–5]	0.19	0.65	0.68	0.54
Extent of youth involvement in the activity: females	3.35 (1.01)	[1–4]	0.12	0.56	0.65	0.65	3.04 (1.01)	[1–5]	0.21	0.67	0.46	0.21
Women friendliness in reducing drudgery	**2.72 (1.03)**	[1–4]	0.13	0.57	0.54	0.51	3(1.38)	[1–5]	0.23	0.71	0.57	0.3
Women friendliness- available to women in their settings	3.05 (0.92)	[1–5]	0.13	0.57	0.46	0.54						
Women friendliness- accessible to women in their settings	2.98 (1.06)	[1–5]	0.14	0.59	0.3	0.46	3.37 (1.25)	[1–5]	0.17	0.62	0.72	0.17
Women friendliness- affordable to women in their settings	3.04 (0.82)	[1–5]	0.14	0.59	0.44	0.47	**3.48 (1.15)**	[1–5]	0.21	0.68	0.46	0.9
Women friendliness- socially acceptable to women in their settings	3.65 (1.06)	[2–5]	0.15	0.61	0.18	0.32	1.67 (1.21)	[1–5]	0.23	0.7	−0.31	0.8
Women friendliness- lower technical skills needed to implement the practice by women in their settings	3.25 (0.85)	[1–5]	0.15	0.62	0.16	0.22	1.94 (1.16)	[1–4]	0.21	0.68	−0.43	0.89
c. **One-Health Achievement (OHA)**												
Reduces pest load	3.14 (0.97)	[1–5]	0.36	0.8	0.02	−0.76	3.52 (1.47)	[1–5]	0.57	0.87	0.44	0.63
Addresses nutrient depletion	3.04 (1.16)	[1–5]	0.28	0.73	0.6	0.57	**3.91 (1.46)**	[1–5]	0.55	0.86	0.46	0.7
Addresses soil–water adequacy	2.83 (1.15)	[1–5]	0.29	0.74	0.52	0.5	3.72 (1.54)	[1–5]	0.5	0.83	0.48	0.81
Addresses soil–water pollution	3.0 (1.02)	[1–5]	0.26	0.71	0.62	−0.5	3.13 (1.67)	[1–5]	0.52	0.84	0.6	0.82
Promotes crop-livestock integration	3.07 (1.05)	[1–5]	0.27	0.72	0.69	0.32						
Lowers Greenhouse gas (GHGs) emissions	3.0 (1.02)	[1–5]	0.26	0.71	0.7	−0.18	3.28 (1.34)	[1–5]	0.5	0.84	0.35	0.78
Public Health Implications: contributes to lowering incidences of diseases to humans.	**3.28 (1.03)**	[1–5]	0.26	0.71	0.73	0.9						
Preserves biodiversity	3.04 (0.96)	[1–5]	0.23	0.67	0.84	−0.7	3.83 (1.34)	[1–5]	0.47	0.81	0.56	0.89
d. **End-user friendliness (EUF)**												
Is the practice technically feasible to male smallholder farmers?	**3.61 (0.62)**	[2–5]	0.29	0.55	0.67	0.63						
Is the practice technically feasible to female smallholder farmers?	3.32 (0.85)	[1–5]	0.37	0.64	0.5	0.87						
Is the practice cost effective during it implementation for male farmers?	3.37 (0.79)	[1–5]	0.29	0.55	0.72	0.47						
Is the practice cost effective during it implementation for female farmers?	3.33 (0.85)	[1–5]	0.21	0.44	0.83	0.5						
e. **Enabling Environment (EE)**												
Access to local institutions (information and knowledge to support uptake): females							2.22 (1.53)	[1–5]	0.89	0.98	0.94	0.95
Access to local institutions (information and knowledge to support uptake): males							**2.28 (1.6)**	[1–5]	0.89	0.98	0.94	0.96
Farmers investment capacity: ability to commit resources by female farmers							2.02 (1.36)	[1–5]	0.88	0.98	0.96	0.97
Farmers investment capacity: ability to commit resources by male farmers							2.2 (1.56)	[1–5]	0.89	0.98	0.92	0.96
Market linkage: Current knowledge and skills to implement the practice -females							2.02 (1.47)	[1–5]	0.9	0.99	0.91	0.91
Market linkage: Current knowledge and skills to implement the practice -males							2.04 (1.49)	[1–5]	0.9	0.98	0.92	0.92

(*continued on next page*)

Table 3 (*continued*)

Latent constructs and indicators	Farmers						Advisors					
	mean (SD)	min–max	avg. inter-item corr.	alpha	FL	OL	Mean (SD)	min–max	avg. inter-item corr.	alpha	FL	OL
Technical feasibility: presence of service providers to support adoption-females							2.13 (1.49)	[1–5]	0.88	0.98	0.95	0.97
Technical feasibility: presence of service providers to support adoption-males							2.17 (1.51)	[1–5]	0.88	0.98	0.94	0.97

3.28 and SD 1.03). The advisors considered bundled practices that addressed nutrient depletion with a mean of 3.91 (high importance) and standard deviation of 1.46.

End-User Friendliness (EUF) had a significant intra-rater agreement among farmers with a rating of 0.4 ($p \leq 0.001$). This is a moderate agreement according to Viera and Garrett (2005). For farmers, end-user friendly CSA and CIS practices that were technically feasible (took care of the current knowledge and skills to implement among the male smallholder farmers) ranked with a mean of 3.61 (medium to high importance) and a standard deviation of 0.62 as shown on Table 2. The agreement among advisors for the Enabling Environment (EE) was 0.69, representing a substantial agreement in accordance with Viera and Garrett (2005) classification of Kendall's coefficient of concordance. CSA and CIS practices that created an enabling environment that promoted access to local institutions – information and knowledge to support uptake among the males was ranked high with a mean and standard deviation of 2.28 and 1.6, respectively. In the 1 to 5 ranking criteria provided for the rankers, this would mean even though the item ranked high among other items, it was still considered of low importance. Generally, all items of EE were considered of low importance by the advisors. The next section discusses the results of the Partial Least Square SEM output.

4.2. Bundling of CSA-CIS Technologies

4.2.1. Indicator reliability

Table 3 shows the results of internal consistency, indicator reliability and convergent validity disaggregated by farmer and advisor ratings. Results showed that farmers considered all the 5 pillars except for Enabling Environment which was considered high among advisors. Farmers considered increased productivity, low associated drudgery, tendency to reduce disease incidence, and practically feasible to male farmers were considered important within the 4 main pillars. This indicates the relevance of increase yields and the ability to improve nutrition and health. Advisors considered access to information on CSA-CIS technologies under enabling environment and confirms the role of information of CSA-CIS technologies for easy usage. These results were confirmed by the hypothetically-defined constructs since inter item correlations were in the region of 0.15 to 0.50 – quite acceptable according to Clark and Watson (1995). However, Enabling Environment specifically on technical feasibility of a technology, Farmers investment capacity among others were high, and were specific to advisors. Farmers had Cronbach's alpha of between 0.4 and 0.7 while advisors ranged between 0.6 and 0.9. The thresholds for alpha as a reliability measure should be between 0.70 and 0.90 and may be as low as 0.60 in exploratory research with maximum being 0.95 to avoid indicator redundancy (Dijkstra and Henseler, 2015).

The Factor loadings (FL) and the outer loadings (OL) were further considered, and results as presented on Table 3, showed farmer's factor loadings ranged between 0.2 and 0.8 while advisors ranged between 0.3 and 0.8. Since our study is exploratory, and considering the nature of the frequency distributions, we used the recommended stringent cut-offs between 0.32 (poor), 0.45 (fair) to 0.71 (excellent) to consider indicators for trimming (Tabachnick and Fidell, 2007). However, following Shevlin (2017) the few fallible indicators of our latent constructs with low factor loadings appropriate to correct for estimation and measurement errors. Consequently, indicators that did not perform well are factored in by lower weights (Barroso and Cepeda-carrion, 2010). It may be concluded that the study achieved the minimum level of reliability of the various pillars of CSRI.

4.3. Fornell-Larcker and the Heterotrait-Monotrait (HTMT) Criterion structural measurements of uniqueness of indicators

Based on Farrell, (2010) validity assessment criteria, correlation between and among the pillars were assessed and presented in Table 4 below. The well-known Fornell-Larcker criterion is frequently used but, critiqued for being a bit unsuitable on conceptual and empirical grounds (Farrell, 2010). Nonetheless, we present its results together with the recently developed Heterotrait-Monotrait (HTMT) ratio of correlations whose robustness is confirmed in many studies (Farrell, 2010; Sarstedt et al., 2022).

As shown in Table 4 below, the square root of each AVE is in the diagonal (bold) and the correlation coefficients (off-diagonal) for each of the evaluated construct in the relevant rows and columns. For farmers, all the 5 indicators are highly correlated among themselves except for GSI and CSRI which recorded a coefficient of 0.82. This indicates that, a high level of agreement among farmers in terms of their climate readiness to mitigation, adaptation and productivity. The small difference of 0.05 is ignorable (Ab Hamid et al., 2017). On the other hand, there was a high level of correlation among the indicators except for EE (0.84) and GSI (0.52). EE and GSI recorded low correlation coefficients among itself compared to higher relationship between EE-GSI, EE-CSRI, and GSI-CSRI. This confirms an acceptable and high convergent validity based because the Fornell-Larcker criterion does not reliably detect discriminant validity issues (Henseler et al., 2015; 2016).

4.4. Empirical Application of the Climate-Smart Readiness Index (CSRI)

4.4.1. Relationship between CSRI and its drivers

Results of the ordinary least square (OLS) regression between CSRI and the other latent variables is shown in Table 5 below. Evidently, for farmers, a unit increase of the OHA pillar was associated with a highly positive and significant 0.526 unit ($p \leq 0.001$) increase in the CSRI. This implies that CSA and CIS bundled practices that form OHA such as reduced pest load, addressed nutrient depletion, soil–water adequacy, soil–water pollution, promoted crop-livestock integration, lowered Greenhouse Gas (GHGs) emissions, preserved biodiversity towards lower incidence of human disease mattered in predicting OHA that was highly associated with CSRI. Farmers ranked items that reduced pest loads and contributed to the lowering incidences of diseases to humans high. Findings for advisors revealed that, Enabling Environment (EE) was associated with a positive and significant (0.562 units, $p \leq 0.001$) increase in CSRI.

Enabling Environment (EE) item associated with CIS (information and knowledge to support uptake CSA) ranked high and can be attributed to the essential role of CIS as a decision support tool among advisors and hence contributing to CSRI prediction. A previous study in this location found that Participatory Integrated Climate Services for Agriculture (PICSA) enables advisors to participatorily work with farmers,

Table 4
Fornell-Larcker criterion of discriminant validity.

Construct	Farmers					Advisors				
	CS	EUF	GSI	OHA	CSRI	CS	EE	GSI	OHA	CSRI
CS	**0.65**					**0.963**				
EUF	0.12	**0.69**	–	–	–	–	–	–	–	–
EE	–	–	–	–	–	0.88	**0.95**			
GSI	0.57	0.42	**0.52**			0.69	0.84	**0.52**		
OHA	0.012	0.32	0.23	**0.78**		0.36	0.51	0.49	**0.78**	
CSRI	0.55	0.67	0.82	0.64	**0.82**	0.89	0.98	0.87	0.63	**0.69**

Table 5
Regression coefficients of association between CSRI and other latent constructs.

CSRI	Farmers			advisors		
	Coef.	Std. Err.	P > t	Coef.	Std. Err.	P > t
CS	0.151	0.009	0.000	0.217	0.008	0.000
GSI	0.395	0.010	0.000	0.159	0.007	0.000
EUF	0.292	0.009	0.000			
EE				0.562	0.011	0.000
OHA	0.526	0.009	0.000	0.185	0.004	0.000
_cons	0.000	0.008	0.995	0.004	0.004	0.326

considering their local settings, indigenous weather knowledge and socio-cultural aspects (Dayamba et al., 2018). For farmers, CSA pillars seem to score poorly and contribute less to their CSRI score whereas advisors seem to score poorly on OHA as a predictor for CSRI.

4.4.2. Role of CSA and CIS technology to CSRI

The latent variable scores indicates that perspectives on evaluation of technological contributions to the CSRI and to the pillars vary among farmers and advisors (Fig. 2). Advisors give more relevance to agroforestry, biocontrol (such as black soldier fly and pheromone traps), biopesticides (such as neem extract), while farmers gave varied and lower weights across the four pillars with only 8 out of 25 CSA and CIS technologies having positive scores. Farmers consider agroforestry as a strong contributor to achieving CS, GSI, OHA while advisors give more weight to enabling environment. Across all four pillars and the CSRI, farmers prioritized pest and disease tolerant varieties compared to advisors. Vine multiplication technology, specifically with hydroponics received same agreement for both advisors and farmers in terms of the four pillars and the CSRI.

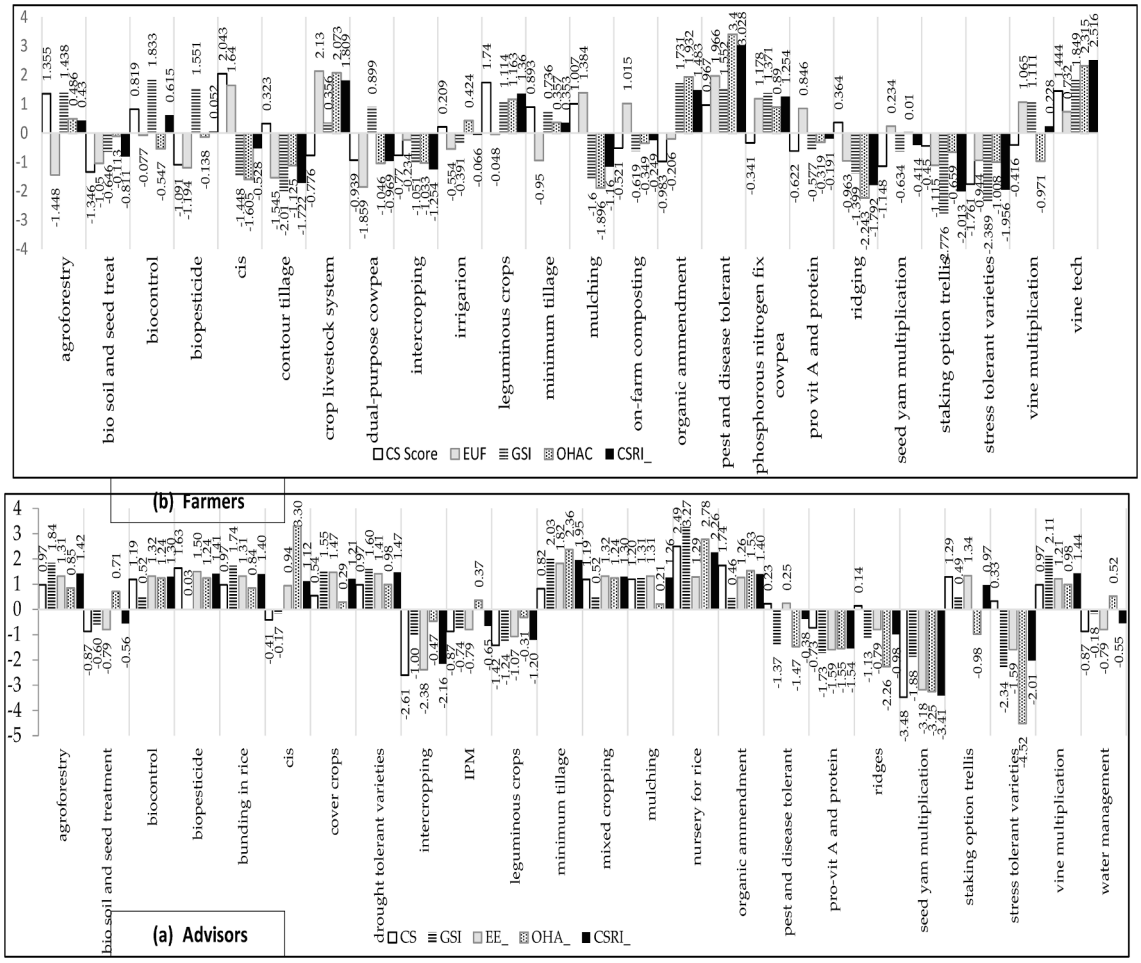

Fig. 2. Latent variable scores against CSA/CIS technologies.

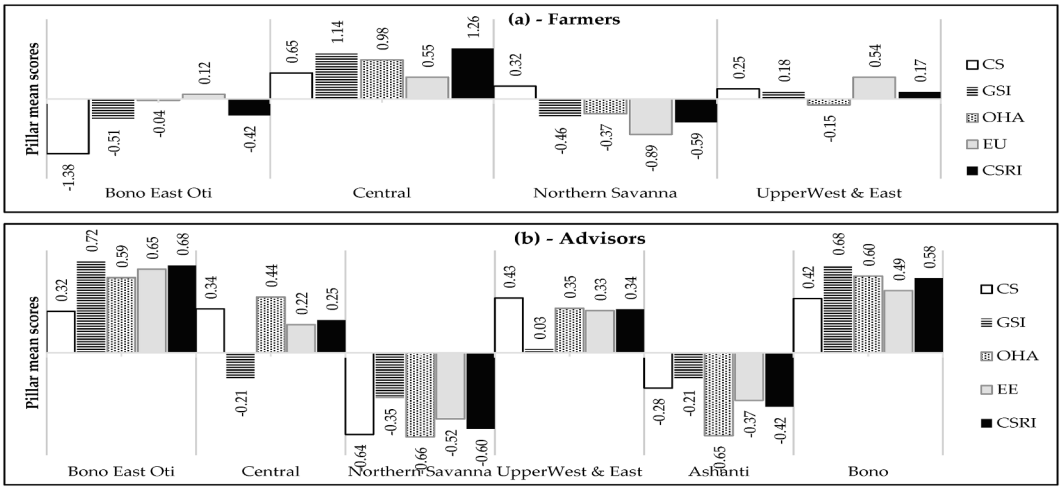

Fig. 3. Summary of pillar scores disaggregated by location for (a.) farmers and (b.) advisors.

4.4.3. Role of geographical based locations on climate readiness

As shown on Fig. 3(a) and (b) respectively, Bono East, Oti, Northern, Savanna, and North East had the least scores for farmers with negative CSR. CSR score was positive for Central, Upper West, and Upper East regions. For the advisors, pillar scores were generally positive for all the regions except for the Northern and Savanna regions. CSR scores were also positive for Bono East, Oti, Central, Upper, West Upper East and Bono but negative for Northern, Savanna and Ashanti.

Northern Savanna had negative ratings for all the pillars for both farmers and advisors and this implies that both farmers and advisors have other criteria as a preparedness mechanism for climate readiness.

5. Implication for climate change mitigation policy

Prioritization and bundling of CSA and CIS technologies and practices is based on the utility derived from the usage and hence influences farmers climate readiness index. Farmers and advisors' values, beliefs and norms further explain the behavioral and socio-economic factors underpinning farmers' climate-smart readiness in terms of Climate Smartness (CS) score, Gender and Social Inclusion (GSI), One-health Achievement (OHA), End-User Friendliness (EUF) and Enabling Environmental (EE). This further reflects the underlying Climate-Smart Readiness Index (CSRI) construct for bundled practices and provides a framework to develop the concept of climate-smart readiness.

There is fundamental difference between farmers and advisors' ratings on CSA and CIS technologies based on their respective varied roles.

Generally, both farmers and advisors have agreed to the critical role of Climate Smartness (CS), Gender and Social Inclusion (GSI) and One-Health Achievement (OHA) in terms of ensuring soil, water, plant, and animal in suing specific bundles. This enhances sustainability and efficient use of resources at all levels. Further to this, farmers prefer end-user friendliness of bundled CSA-CIS technologies attributed to reduce the drudgery and somehow tedious application requirements of bundles. This therefore calls for identification of location specific easy-to-use bundles involving all value chain actors. Advisors have identified enabling environment within which bundles can be efficiently used and collaborates with farmers choice of user-friendliness as an additional criterium for prioritization and bundling in Ghana.

Farmers consideration of One Health for CSA-CIS technology prioritization and bundling confirms the critical role of sustainable soil, water, plant and animal health in achieving adaptation, mitigation and increased productivity. Farmers are concern about food safety and increased yield due to the high level of prioritization of vine technology, and pest and disease tolerant varieties wile an Enabling Environment (EE) seemed important for advisors while advisors have broader concerns.

CRediT authorship contribution statement

Osman Tahidu Damba: . **Collins Odhiambo Ageyo:** . **Fred Kizito:** Conceptualization, Data curation, Supervision, Writing – original draft. **Powell Mponela:** Data curation, Writing – original draft. **Stephen Yeboah:** Data curation, Writing – review & editing. **Victor Attuquaye Clottey:** Conceptualization, Data curation, Writing – original draft. **Birgitta Adoma Oppong-Mensah:** Data curation, Writing – review & editing. **Jules Bayala:** Methodology, Writing – review & editing. **Faustina Obeng Adomaa:** Data curation, Writing – review & editing. **Mustapha Alasan Dalaa:** . **Francisca Martey:** Visualization, Writing – review & editing. **Sophia Huyer:** Methodology, Validation. **Robert Zougmore:** Funding acquisition, Supervision, Writing – review & editing. **Ghislain Tepa-Yotto:** Funding acquisition, Supervision, Visualization, Writing – review & editing. **Manuele Tamò:** Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ghislain Tepa-Yotto reports financial support was provided by We acknowledge tInternational Development Association (IDA) of the World Bank to the Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) project (AICCRA, P173398). The remaining 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.

Data availability

Data will be made available on request.

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Appendix

Table A1. Internal consistency measures of the measurement model.

Construct	Farmers				Advisors			
	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
CSRI	0.54	0.54	0.81	0.68***	0.92	0.98	0.93	0.47***
CS	0.55	0.60	0.65	0.42	0.96	0.96	0.87	0.89***
GSI	0.58	0.62	0.73	0.27	0.62	0.79	0.60	0.27***
OHA	0.75	0.53	0.40	0.61***	0.87	0.88	0.90	0.61***
EE					0.99	0.98	0.89	0.89***
EUF	0.62	0.74	0.72	0.41				

Internal consistency and convergent validity of indicators

Internal consistency reliability refers to the extent to which the proposed indicators that measure the same construct are correlated with each other. As shown in Table A1, the Cronbach's alpha for the latent constructs for farmers were 0.62 for the End-User Friendliness (EUF), 0.75 for One-Health Achievement (OHA), 0.58 for Gender and Social Inclusion (GSI), 0.55 for Climate Smartness Score and 0.54 for Climate-Smart Readiness Index (CSRI). Evidently, the model suffers from the major limitation of Cronbach's alpha as it assumed that all the study's indicator loadings would be the same for the population (tau-equivalence) as manifested in the lower reliability values of the alphas (Dijkstra and Henseler, 2015; Hair et al., 2021). On the other hand, the alphas of the advisors were on the highest range of 0.9. Nonetheless, the alpha presents an acceptable lower end approximation of the study's true internal consistency reliability. The upper end of consistency is presented by the higher values of composite reliability of between 0.4 for OHA and 0.8 for CSRI among farmers; and values between values between 0.6 for GSI and 0.93 for CSRI among advisors. The 0.60 and 0.70 ranges are acceptable in exploratory research while 0.70 to 0.90 range would be considered satisfactory to good (Diamantopoulos et al., 2012). In the advisor's ratings, the values seem a bit redundant and may affect the construct validity but fall within the acceptable range. The reliability coefficient (ρA) falls between these two extremes and currently considered a good measure of internal consistency (Dijkstra and Henseler, 2015). Values above 0.90 (and definitely above 0.95) are problematic, since they indicate that the indicators are redundant, thereby reducing construct validity.

The AVE values that measure convergent validity seem to perform poorly for the construct of Gender and Social Inclusion (GSI). It means the construct explain below 50 percent of the variance that make up the construct. However, the rest fall in the minimum acceptable AVE of 0.50. An AVE of 0.4 is acceptable because the composite reliability was higher than 0.7 for the GSI construct. Thus, the study relies on the Fornell and Larcker (1981), explanation that where AVE is low but composite reliability is high, the convergent validity of the construct is still adequate (Fornell and Larcker, 1981).

Table A2. Bootstrapped and bias-corrected confidence intervals using Hetrotrait-Monotrait Ratio (HTMT) criterion.

Farmers						Advisors				
Construct	Original sample (O)	Sample mean (M)	Bias	2.5 %	97.50 %	Construct	Original sample (O)	Sample mean (M)	2.50 %	97.50 %
CSRI->CS	0.81	0.88	0.06	0.66	0.91	CSRI->CS	0.86	0.86	0.77	0.94
EU->CS	0.41	0.54	0.12	0.20	0.53	EE->CS	0.89	0.89	0.78	0.98
EU->CSRI	0.89	0.94	0.04	0.77	1.00	EE->CSRI	0.95	0.95	0.93	0.97
GSI->CS	0.82	0.86	0.03	0.64	1.00	GS->CS	0.59	0.61	0.47	0.76
GSI->CSRI	1.15	1.13	−0.02	1.12	1.23	GS->CSRI	0.92	0.93	0.87	0.98
GSI -> EU	0.68	0.76	0.07	0.47	0.79	GS -> EE	0.66	0.67	0.54	0.79
OHA -> CS	0.30	0.44	0.13	0.20	0.34	OHA -> CS	0.39	0.41	0.18	0.67
OHA-> CSRI	0.98	0.99	0.01	0.91	1.03	OHA -> CSRI	0.78	0.79	0.69	0.89
OHA -> EU	0.54	0.62	0.08	0.31	0.71	OHA -> EE	0.55	0.55	0.40	0.71
OHA -> GSI	0.73	0.77	0.04	0.57	0.83	OHA -> GS	0.54	0.61	0.44	0.81

In addition to the Fornell-Larcker criterion, Table A2 shows results of the 10,000 bootstrapped confidence intervals. to assess whether the upper bound of the confidence is lower than 1.0 (Henseler et al., 2015). For farmers, the study tests the null hypothesis H_0: HTMT $\geq$ 1 versus the alternative hypothesis that H_1: HTMT < 1. Evidently, the correlation between GSI -> CS, EU -> GSI, GSI -> CSRI and OHA-> CSRI showed lack of discriminant validity because their values fall outside the interval's range. This suggests that these constructs are empirically indistinct. The sensitivity of HTMT method and the fact that we used higher-order constructs could be the reason as explained by Hair et al. (2021). We also suspect the non-problematic issue of collinearity in the GSI items (VIF $\leq$ 3) and the fact that farmer-ratings would be subjected to idiosyncratic factors.

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