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Integrated environment-smart agricultural practices: A strategy towards climate-resilient agriculture

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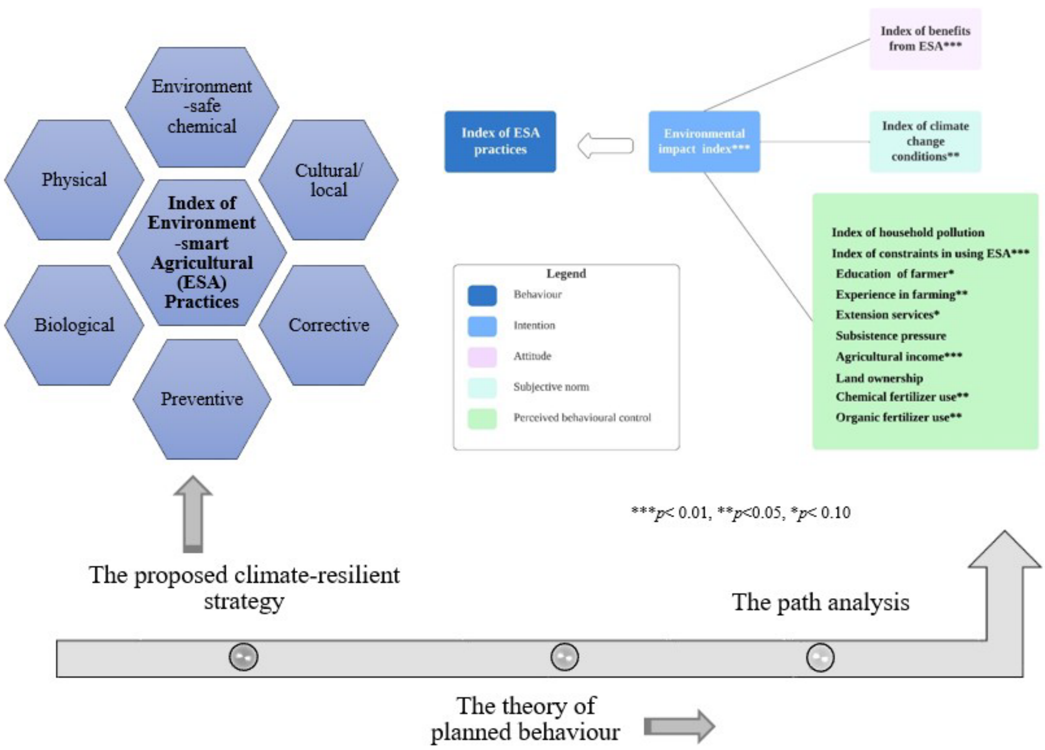
Abstract: This article proposes an integrated farming approach, namely environment-smart agriculture (ESA) that determines the climate-resilience potential of a farm. A composite index is formulated including various environment-smart agricultural practices (IEP) that focus on the five most affected target areas of farm environment and climate. The IEP is then validated by analysing the on-farm environmental impact and farmers' behaviours in the underlying *theory of planned behaviour* (TPB) framework. The TPB components, *attitude* and *subjective norm,* are defined by the index of benefits from the ESA, and the index of experienced climate change conditions respectively, while *perceived control* corresponds to the index of constraints in adopting ESA and farm-specific agro-economic and socio-economic attributes. The empirical testing employed a structural equations model (SEM) to estimate the proposed IEP on a sample of 103 farms in two north-western districts of Bangladesh. Results demonstrate that the adoption of integrated ESA practices mitigates post-harvest environmental problems and helps cope with existing climate change conditions. Therefore, farm-level investment in ESA practices, i.e., the use of corrective, preventive, and local standard measures in an integrated way will contribute to the climate-resilience potential of a farm.

JEL classification: Q01, Q15, Q16

Keywords: Agriculture, Environment-smart, Climate-resilient

Graphical Abstract



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1. Introduction

Climate-resilient agriculture is a sustainable approach to food security that simultaneously employs adaptation and mitigation measures (IPCC, 2014). However, increasing agricultural productivity in a changing climate as well as without jeopardizing social and environmental resources remains a major challenge. Sustainable methods including climate-smart agricultural (CSA) technologies aim to yield improvement by reorienting and transforming the existing system for changing climate conditions. (Hammond et al., 2017; Khatri-Chhetri et al., 2017; Lopez-Ridaura et al., 2018; Sain et al., 2017). These adaptation measures are climate-resilient if they could achieve resource management (Sain et al., 2017), reduce GHGs (Greenhouse gases) emissions and improve carbon sequestration (Campbell et al., 2014). This implies that any CSA practice without mitigation abilities can leave multiple adverse impacts on resources, namely soil erosion, fertility reduction, soil, water, and air pollution, fish reduction, biodiversity loss, loss of drinking water, and reduction of social capital. CSA often allows for the intensive use of chemical inputs, modified or high-yielding crop varieties, and machinery (Godfray et al., 2010; Tilman et al., 2011). Residues of chemical inputs are frequently transmitted through the soil to crops and then to humans and animals, and contribute to GHGs emissions (Savci, 2012) and hence increase warming. According to IPCC estimates, there is a possibility of a 25% yield loss by 2050 due to a temperature increase (IPCC, 2014). Changes in the climate can further be influenced by climate-smart agriculture if the adverse impacts of cropping are not controlled. Therefore, it is a paradox whether a climate-resilient strategy could approve an approach that simultaneously improves yield and reduces agro-ecological risks of pollution, erosion, and reduction of resources. More importantly, a resilient ecosystem requires an evaluation of both *services and disservices* generated in that system (Toledo-Gallegos et al., 2022). Hence, we argue here that an integrated farming practice is required and that environment-smart agriculture (ESA) is a viable, adaptable and climate-resilient strategy.

By definition, ESA is a holistic approach comprising a set of corrective and preventive farming practice measures. A climate-resilient farm can absorb after-harvest stress on the farm environment and the atmosphere (or climate). The ESA approach aims to limit GHGs emissions from farm chemicals by controlling their adverse impacts on-farm soil and water and by improving farmer awareness of, and willingness to manage, environment-depleting farming activities. Sustainable growth in yield is an inherent aim of any agri-business and is conditional upon farmers' environmental awareness and perception of climate change impacts. An integrated impact management approach should deal with soil, water, and GHG emission-related impacts, crop and human health impacts, and farm nuisance. Such an approach necessitates the aggregation of corrective, preventive, physical, biological, traditional, and environment-friendly chemical practices of farming. By employing ESA, a farm can become gradually resilient and achieve food sovereignty (Altieri and Nicholls, 2017, Sabiha and Rahman, 2018). Because of its composite nature, ESA can be considered an alternative pathway toward both climate-smart and climate-resilient agriculture. Notwithstanding, ESA has not been salient in mainstream policy frameworks and among academics. Farmers may be aware of climate change adaptation measures including CSA and even the impact of cropping in a climate change scenario; however, it is not explained how the variability in climate parameters, impacts of climate change, and farmers' adoption of environment-smart agricultural measures are connected. This study assesses such inter-linkages empirically. We argue that farmers decide their ESA practices and adaptations optimally perceiving the impact of these measures on both cultivation practices and the local environment. In this study, farmers' perceptions are analysed by employing the conceptual framework of the *theory of planned behaviour* (TPB) introduced by Ajzen and Madden (1986). It is hypothesized that a farm with a higher level of ESA adoption will exhibit fewer on-farm environmental impacts and hence become more climate-resilient. The novelty of this study relies upon the conceptualization of the ESA index by conducting a pathway analysis and by employing TPB as a theoretical framework for understanding that pathway. The proposed ESA index can be used as an alternative tool to measure the *extent* of and *potential* for a farm operating under both environment-smart and climate-resilient modes. The illustration of the proposed ESA approach uses data from a comprehensive survey covering two agro-ecological zones in Bangladesh. In Bangladesh, the intensification practice to cultivate high-yielding crops has been facilitated by both policy provisions and commercialisation in input trading since 1980 (Salim and Hossain, 2006). This transition was also popularized because of its cropping suitability in less-controlled environmental conditions (Alauddin et al., 2021). Similarly, to reduce cropping vulnerability to climate change and extreme events, CSA and other adaptations are largely institutionalized in the country. However, there is not sufficient evidence that CSA and other on-farm adaptation measures can mitigate negative environmental impacts.

The remainder of this paper is organized as follows. Section 2 gives an overview of the literature on sustainability indicators in evaluating climate-resilient agriculture. This is followed by the analytical framework in Section 3 and Section 4 provides results and their discussion Section 5 concludes the study with the relevant policy suggestions.

2. Overview of the evaluation of climate-resilient interventions

In climate-resilient and smart agriculture literature, much attention has been given to identifying sustainability indicators and indices including economic and non-economic indicators. Referring to IPCC (2014) and FAO (2010) the threefold objectives of an agricultural system to be climate-resilient are sustainability in production, climate change adaptation, and climate change mitigation. An economic evaluation of a particular intervention can be performed based on the cost of implementation, productivity, and farm income after adopting a technology. This is evident in understanding the economic viability of most CSA interventions in past studies (Hammond et al., 2017; Khatri-Chhetri et al., 2017; Khatri-Chhetri et al., 2019; Makate et al., 2019; Mwongera et al., 2017; Sain et al., 2017). Farmers put a high score for interventions on higher adaptation potential, cost-effectiveness at an individual level, and even consider benefits for the whole community (Wassmann et al., 2019). However, economic stress and credit inaccessibility are two important barriers to climate change adaptation and farming (Apataet al., 2009; Mertz et al., 2009; Sarker et al., 2013; Alauddin et al., 2020). Lopez-Ridaura et al. (2018) argue that not all CSA technologies are equally cost-effective or make all households evenly food-secure. The authors observed that conservation agriculture is preferred by wealthy farmers. Income and farm size can be potential indicators for assessing farmers' responses to climate-resilient agriculture. However, Koirala et al. (2022) observed that small farms are more responsive to adaptation measures than large farms. The authors argued that economic objectives alone are not suitable estimates of agricultural input impacts due to farmers' heterogeneity in their motivations and cropping pattern. In addition to this, CSA requires more labour (Sain et al., 2017), and uptake of CSA largely depends on off-farm income (Hammond et al., 2017). Therefore, the credibility of CSA as cost-effective and considerate of farmers' adaptive capacity is arguable.

Sustainability measurement has developed concern about the environmental impacts of smart technologies. Quantitative measurement can approve of an approach or a system (Sands and Podmore, 2000) and hence evaluation relies largely on constructing an environmental sustainability index or an environmental index, and environmental performance indicators.

While assessing environmental sustainability, most studies include a large number of sub-indices or partial indices; namely the use of agro-chemical inputs including fertilizers, herbicides, and pesticides, soil properties, water availability for irrigation, and crop health. For instance, Jackson et al. (2011) argue that the efficient use of water and energy makes a farm more climate-resilient. Alauddin et al. (2020) estimated that the use of a water-saving irrigation technology could reduce irrigation frequency and cost of irrigation. Thus, the amount of water used, management of groundwater sources, and water quality are used to measure environmental sustainability (Bui et al., 2019) which can additionally ensure economic efficiency. to A soil quality sub-index includes its nutrients, fertility, and toxicity levels as indicators (Sulewski and Kłoczko-Gajewska, 2018; Taylor et al., 1993). Taylor et al. (1993) include integrated pest management and weed control by using spraying and applying non-chemical techniques as farm sustainability sub-indices. Soil quality impacted by fertilizer application is the most important determinant of agricultural productivity and sustainability of the environment (Nambiar et al., 2001). As Lipper et al. (2014) argue an increase in soil quality implies that soil carbon is reduced. Water and wind erosion, toxic components, salinization, and declining soil nutrients may determine the state of soil quality. Soil determinants are *production potential indicators* and the impacts on soil, water, air, and biodiversity are *environmental perception indicators* (Sulewski and Kłoczko-Gajewska, 2018). Using a correlation matrix, these researchers found a positive correlation between these indicators and farmers' uptake of efficient agricultural management. Sands and Podmore (2000) argue that the existing resource position and the efficiency in the cropping system are important factors in the sustainability of a system. This implies that perceiving the status quo of physical resources and the impact of employing any method on these resources could help farmers shape awareness and determine adoption behaviour. Land ownership and experience in farming could measure the resource accessibility of a farmer. In addition, the cropping method is also included as a comprehensive measure of sustainability. As a sustainable method of cropping, the use of organic fertilizers contributes significantly to GHGs emission reductions and to improving carbon and methane sequestration (Altieri and Nicholls, 2017). Even efficient management in chemical input application and water for irrigation can help maintain soil quality which eventually affects fertility as Nambiar et al. (2001) argue. These studies suggest that the impacts of any smart agricultural practice on air, water, and soil resources indicate the resilience of these resources.

Emissions and impacts are usually local in agriculture, agro-processing industry, and residue and waste management systems. Changes in weather patterns or extreme climate events locally affect agricultural yield, crop health, and farm environment. However, the early policy discussions focused on climate change as a global issue and provided generalized solutions for agricultural sustainability. Some CSA technologies may be suitable for local climate change conditions, e.g., drought-tolerant crops and rainwater harvesting in areas with intense summer and inadequate rainfall respectively (Hammond et al., 2017; Khatri-Chhetri et al., 2017). These measures are locally suitable concerning crop choices and yield increase only. Furthermore, most climate-smart technologies are capital and water-intensive (Alauddin and Quiggin, 2008) and accrue limited or no concern about mitigation, e.g., technology that produces low emission of GHGs and fewer impacts on resource quality (Hammond et al., 2017; Sain et al., 2017). Except for efficient irrigation technologies, inputs and farm operations being climate-resilient did not receive much attention. As Oerke (2006) demonstrated, even integrated pest management techniques could not reduce crop vulnerability to pests and weeds. The reason may be that farmers do not perceive the impacts of using these technologies on climate change (Wassmann et al., 2019). Farmers are even less likely to adopt CSA involving mitigation efforts (Khatri-Chhetri et al., 2017). Farmers must understand the cause-and-effect relationships while adopting any smart agricultural practice. To be precise, it is required to analyse farmers' perceptions about how farms are exposed to on-farm environmental impacts and climate change impacts after adopting smart practices. In addition, farmers' responses may be variable to an integrated impact management strategy and motivations for adopting such a strategy. Therefore, the specific objectives of this study are: (i) to develop a composite index of environment-smart agricultural practices (IEP), (ii) to validate the IEP theoretically by analysing farmers' perceptions and behaviour, and (iii) to illustrate the proposed IEP as a tool to measure the resilience-potential of farms.

3. Methodology

3.1 Theoretical framework

This study employs the *theory of planned behaviour* (TPB) originally developed by Ajzen and Madden (1986), to evaluate the pathway of ESA practices. TPB framework helps to understand and assess individual social and psychological behaviour in multiple disciplines (Despotović et al., 2019; Rezaei et al., 2019). TPB analyses patterns of subjective behaviours towards an action. Originally derived from the *theory of reasoned action* (*TRA*), in the TPB framework, any action or behavioural intention is depicted as the optimum choice made by an individual

(Ajzen and Madden, 1986; Madden et al., 1992). In both the TRA and TPB frameworks, the intention is postulated as the driving force in formulating behaviour. The decision-making process in TPB follows a strategic flow that is explained by three independent latent variables; namely *attitude*, *subjective norms,* and *perceived behavioural control* (Ajzen and Madden, 1986). This framework has been used in explaining farmers' different agronomic practices, i.e., agricultural input, namely fertilizer and manure use (Daxini et al., 2019), pollution control and management (Wang et al., 2019), pest management (Despotović et al., 2019; Rezaei et al., 2019), soil conservation methods (Wauters et al., 2010), environmental consciousness and impact (Hoogendoorn et al., 2019), minimum tillage and row planting (Zeweld et al., 2017), and agri-environmental diversification (Sutherland et al., 2016). In addition to explaining farmers' attitudes about smart agriculture, these studies have tested TPB links between components. TPB framework has been largely used in the perception-based agri-environmental analysis because it allows the identification of the link between awareness and adoption. This framework includes the social and psychological or cognitive factors influencing the adoption of a sustainable action (Zeweld et al., 2017; Lin and Wang, 2021). These *intrinsic* factors may even influence the economic profitability of a sustainable approach and improve its diffusion (Bopp et al., 2019). Therefore, it is possible to address the motivational factors, including economic and cognitive factors, which can shape farmers' environmental orientations and optimize on-farm resource and input utilization. However, it is also possible that intention does not always drive behaviour. For instance, in Lin and Wang (2021), intention does not increase the low-carbon travel of urban residents. This suggests that the attributes and construction of TPB components may influence an individual's perception and choices consequently.

In our analysis, the composite index of environment-smart agricultural practices (IEP) is the *behvaiour* of an individual farmer and the intensity of on-farm environmental problems (EII) is defined as the *intention*. Theoretically, intention induces action or a certain behaviour. However, to analyse any post-ESA adoption behaviour, the nature of this link has been modified. It is postulated that a farmer is motivated to adopt ESA if the farmer perceives that employing ESA would limit on-farm environmental problems (indicating a reciprocal association). Following Ajzen and Madden (1986), *attitude*, i.e., the 'index of benefits from ESA' which is the outcome of ESA, is defined as the advantages of the ESA for production and farm resources. *Subjective norm* captures social restraints (Ajzen and Madden, 1986; Daxini et al., 2019) which is an indifferent factor at the community level. Climate change and its impacts are spatially distinguishable; hence they are included as *subjective norms* and named the 'index of climate change condition'. Finally, higher perceived control implies better command over resources and corresponding behavioural intention (Ajzen and Madden, 1986). Thus, perceived behavioural control can capture individual adaptive capacity. Adaptive capacity is bottom-up or community-level knowledge that demonstrates actual adaptation (Smit and Wandel, 2006). Actual adaptation is constrained by resource availability and access at the household level, therefore socio-economic and institutional factors and agricultural input accessibility are included as perceived control. The main motivation for using this framework and the novelty of this study is that a holistic index of on-farm negative environmental impacts (EII) is used to indicate *intention*, which tends to drive multiple environment-smart agricultural practices (IEP), the *behaviour* component. This framework also includes household characteristics, climate change conditions, and on-farm environmental impacts. In this paper, TPB is used mainly for model identification and for validating the proposed IEP as an alternative tool to measure the resilience potential of a farm. Therefore, TPB components are not predicted. In addition to this, TPB components are not included as latent variables so that farmers' behaviour towards ESA can be explained by the observed exogenous variables separately (Figure 1). Table 1 shows the components, variables, and expected signs of relationships.

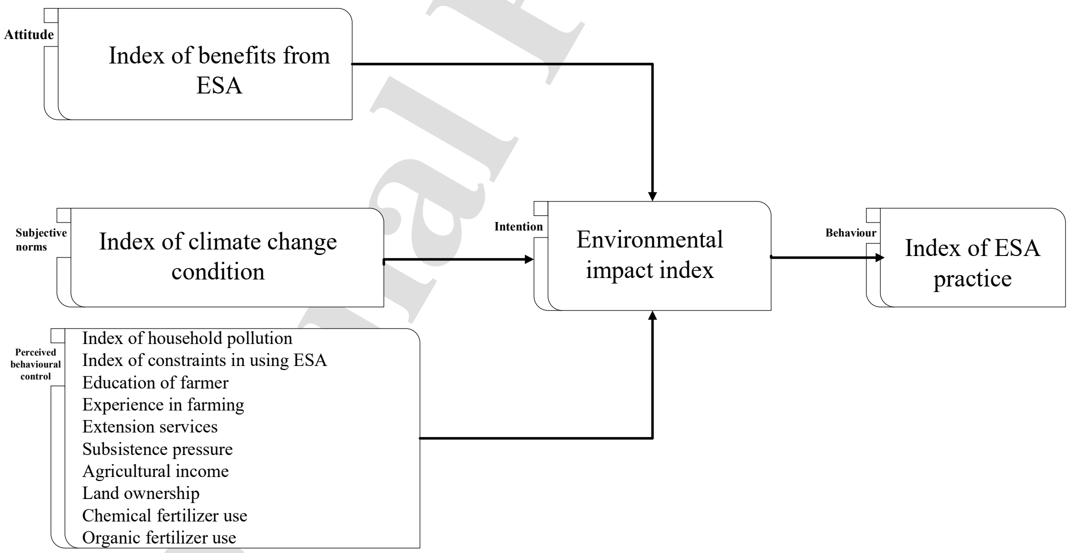

Figure 1: Components of TPB and their interrelationships in understanding ESA behaviour

Table 1: Variable selection in the TPB framework and the expected sign of relationships

Variables	Expected sign
a. Intention → Behaviour	
Environmental impact index → Index of ESA practice	Negative
b. Attitude → Intention	
Index of benefits from ESA → Environmental impact index	Negative
c. Subjective norm → Intention	
Index of climate change condition → Environmental impact index	Positive
d. Perceived behavioural control → Intention	
i. Index of household pollution→ Environmental impact index	Negative
ii. Index of constraints in using ESA → Environmental impact index	Positive
iii. Education of farmer → Environmental impact index	Negative
iv. Experience in farming → Environmental impact index	Negative
v. Extension services → Environmental impact index	Negative
vi. Subsistence pressure → Environmental impact index	Positive
vii. Agricultural income → Environmental impact index	Negative
viii. Land ownership → Environmental impact index	Negative
ix. Chemical fertilizer use → Environmental impact index	Positive
x. Organic fertilizer use → Environmental impact index	Negative

3.2 Index construction and indicators of TPB components

Environment-smart agriculture (ESA) aims to limit the environmental impacts of agriculture and to aid in managing climate change impact on agricultural production. We propose an alternative approach that can be used to measure the farm-specific composite index of ESA practices (IEP) (Figure 2). The approach is named an integrated impact management approach that integrates important methods of managing on-farm environmental impacts. These are physical, chemical (safe to the farm environment), biological, local/cultural standards, and preventive and corrective methods. These methods satisfactorily target those impact areas that are mostly affected by chemical-intensive agriculture. For each method, we have identified the respective impact management techniques. Then we compute the weighted sum of the numbers of techniques under each selected method as the index of ESA practices (IEP). A higher weight is assigned to a given method that comprises a higher number of techniques. In this case, we give 0.5 incremental weights between 0 and 2. The resulting score of the IEP, therefore, implies that farms with a high IEP contribute more by managing agriculture-induced environmental impacts. The index name, their selected components, and the respective methods of constructing the index and its formula are presented in Table 2. We formulated the

Environmental impact index (EII) and other indices following Sabiha et al. (2016). Table 2 also includes the calculation details of these indices.

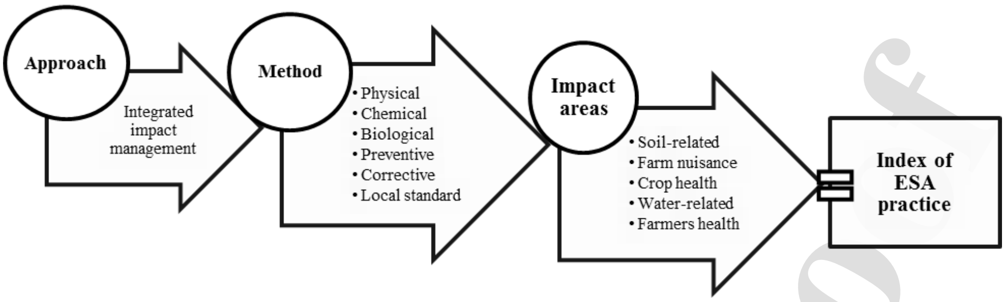

Figure 2: The process of conceptualizing ESA and constructing the ESA index

Table 2 Names, components, methods and formulas of variable indices

Index name, components and methods	Formula
Environmental impact index (EII): Fertility reduction, pest attack, crop disease, soil erosion, soil hardness, skin problem, soil salinity, soil water holding capacity, waterlogging, water pollution, fish catch reduction, and soil toxicity. Opinion-based item analysis approach: a composite form of impacts mostly experienced by the farmers. Likert five-point scale.	$EII_i = \sum_{z=1}^{12} w_l E_z$ where, w_l = weights, (l= 0,0.2,0.4,0.6,0.8,1) higher the weights, higher the intensity of impact perceived by the farmers. E_z = Likert point for given on-farm environmental impacts after harvest
Index of ESA practice (IEP): Use of physical, chemical, biological, local, preventive and corrective techniques of on-farm impact management. Integrated impact management approach: Weighted sum of the number of environment-smart farming techniques used by a given farmer.	$IEP_i = \sum_{f=1}^{6} \sum w_j M_f$ where, w_j = weights, (j=0,0.5,1.0,1.5,2) higher number of ESA farming techniques used for a given method, higher the weights. M_f= number of farming techniques for a given method
Index of benefits from ESA (IEB): Increase in yield, reduction in irrigation number and cost, reduction in crop disease and insect/pest attack, improvement in soil fertility, soil erosion and soil toxicity condition, reduction in surface/groundwater pollution, and reduction in farmers' health impact. Opinion-based item analysis approach: overall benefits achieved from using ESA practices, Weighted sum of Likert five-point scale.	$IEB_i = \sum_{s=1}^{10} w_l B_s$ where, w_l = weights, (l=0,0.2,0.4,0.6,0.8,1) higher weights, higher degree of benefits received from ESA practices. B_s= Likert point for a perceived benefit of ESA practices.
Index of climate change condition (ICCN): Sudden rainfall, flood/drought, temperature increase, temperature decrease, pre/post-monsoon storm, monsoon storm, and fall in groundwater level. Opinion-based item analysis approach: overall perception of climate change condition. A weighted sum of Likert five-point scale for each component	$ICCN_i = \sum_{d=1}^{7} w_l C_d$ where, w_l = weights, (l=0,0.2,0.4,0.6,0.8,1) higher weights means the higher intensity of the climate change condition. C_d = Likert point for a given observed climate change condition.
Index of constraints using ESA (ICE):	$ICE_i = \sum_{n=1}^{15} w_j T_n$

Limited knowledge of on the environmental consequence of farm chemicals and benefits of the soil test, shortages in soil test equipment, limited access to water-saving irrigation, rise in irrigation cost, an insufficient supply of solar energy, organic fertilizer and shortages in quality seed, and insufficient training facilities on environment-safe farming techniques. Statistical averaging procedure: Weighted sum of the number of constraints using environment-smart farming techniques.	where, w_j = weights, (j=0,0.5,1.0,1.5,2) higher the number of constraints to use ESA farming techniques, higher the weights. T_n = Total number of constraints/difficulties using ESA farming techniques
Index of farmers' household pollution (IHP): House category, sanitation, access to health facility, drinking water source, household energy source, and waste disposal Statistical averaging procedure: Weighted summation of environment polluting household living attribute.	$IHP_i = \sum_{a=1}^{6} w_h a / 24$ where, w_h= polluting activity weights, h = 4 (least), 3 (good), 2 (better), 1(best). a = component attributes

Source: Authors' preparation

3.3 Study area and sample

This study addressed one climate extreme event and the required mitigation pathways. A farm-level household survey was conducted in the western climatic sub-region covering three agro-ecological zones in Bangladesh. Two major administrative areas, i.e., districts fall in this region namely *Rajshahi* and *Naogaon*. These areas are vulnerable to frequent droughts as climate extreme events and consequently severe groundwater depletion (Alauddin and Sarker, 2014). Figure 3 provides the map of agro-ecological zones in Bangladesh including the identification of the study area. Agro-ecological zones (AEZs) are grouped according to cropping and climate conditions, soil characteristics and other topographical features. There are 30 AEZs in Bangladesh and western regions itself in the country has varying in soil fertility level and climatic conditions (GOB, 2020). The most important crops cultivated in these areas are highly irrigated, including grains, cereals, vegetables, and fruits. The intensity of cropping in *Rajshahi* and *Naogaon* amounts to 203% and 202% respectively, while the area under HYV rice production is three times larger in *Naogaon* than in the other region (GOB, 2020). However, soil fertility level and consequently crop yield vary considerably in the selected AEZs. No variation in ESA practices is observed in this study. The reason might be that they experience similar climate change conditions, impact and constraints to using enovironment-resilient technologies. The sampling frame uses the list of the registered farmers under each jurisdiction of the Agriculture extension union offices (AEUOs). The required sample size (the number of farmers who were required to be interviewed in the survey) was calculated following Cochran (1977) and Bartlett et al. (2001). Thus, following a random sampling procedure, a total of 103 agricultural farms were chosen for field survey using a structured questionnaire.

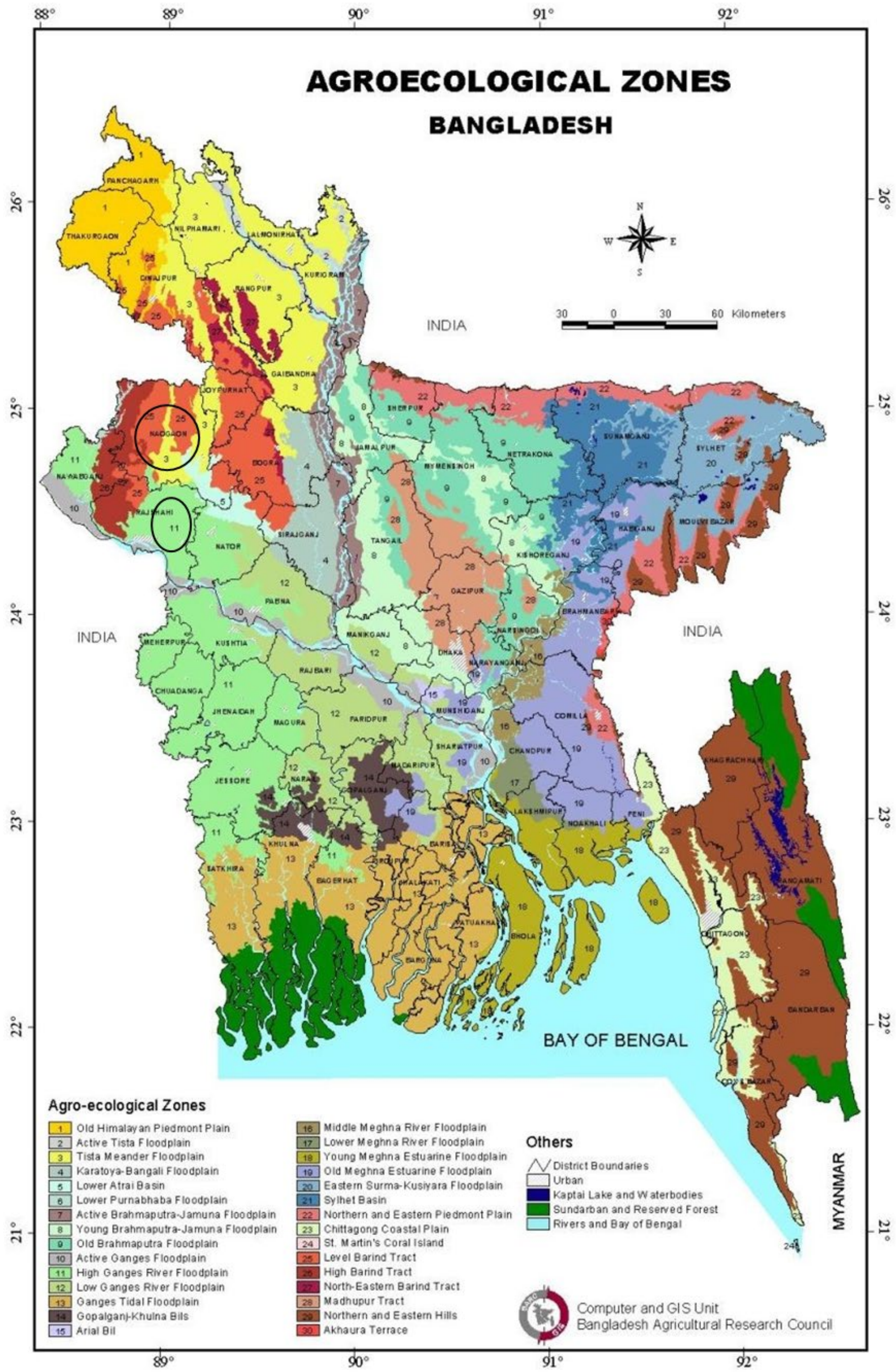

Figure 3: Map of agro-ecological zones in Bangladesh
Note: The black circles indicate the study area.
Source: Retrieved from https://www.bamis.gov.bd/en/page/aezs-maps/

3.4 Data Analysis

Structural equation modelling (SEM) was employed to validate the ESA approach econometrically under the TPB framework. SEM has been increasingly used in social sciences, ecological studies, and human behaviour analyses in the presence of linear multivariate causal relationships (Brito and Pearl, 2012; Fan et al., 2016). A two-step pure and recursive structural model was used for the estimation of path analysis among variables. Path analysis is one way of conducting SEM where causal relationships are motivated by a theory (Holland, 1988). Also, the rationale for using a recursive model is that the causal relationships between variables are hypothesized as uni-directional (Brito and Pearl, 2012). In the first step, the impacts of variables depicting *attitude, subjective norm,* and *perceived control* are estimated on the *intention* variable. In the second step, the reduced model estimates the causal relationship between the *intention* variable and the *behaviour* variable.

4. Results and discussion

4.1 Data description

Table 3 presents the descriptive statistics of computed indices and farm-specific characteristics. The mean values of indices demonstrate that the scenarios of on-farm environmental impact (EII) and climate change condition (ICCN) are large relative to other indices. Farmers in the study area are less likely to perceive benefits from ESA practice as the average value of this index (IEB) is low. Also, the mean value of the ESA practice (IEP) is moderately low, perhaps reflecting the lower level of their environmental perception. The average education level of farmers is at the secondary stage which suggests a poor educational background. However, they are satisfactorily experienced in farming and around 78 percent of their total income comes from agriculture. Approximately 49 percent of farmers have access to extension services which demonstrates poor institutional provision in the study area.

Table 3: Indices/variable data description

Indices/ variables	Mean	Max	Min	St. dev.
IEP	7.62	19.5	0.5	4.43
EII	19.50	60	1	16.37
IEB	9.99	36.6	0.21	9.21
ICE	9.85	29	0.5	7.75
ICCN	13.87	35	2.2	8.86
IHP	0.80	1.95	0.37	0.16
Land ownership (proportion out of total arable land)	0.64	1	0.02	0.38
Education (Schooling years)	7.18	17	0	5.17
Experience (Years)	25.05	50	5	10.47
Extension service (1=yes, 2=no)	1.51	2	1	0.51

Subsistence pressure (proportion of dependent out of total family members)	0.69	0.87	0	0.13
Chemical fertilizer application rate (kg/acre)	77.11	387.5	2.37	65.75
Organic fertilizer (kg/acre)	1197.30	2700	99.92	681.82
The proportion of agriculture out of total income	0.78	1	0.2	0.29

Source: Field survey

4.2 Environmental impact and climate change related attributes in variable indices

4.2.1 Climate change (CC) condition and impact on yield

Table 4 shows the number of farms facing different climate change conditions and, consequently, loss in agricultural production in the study area. Among those CC conditions, sudden rainfall and flood/drought followed by a fall in groundwater level and temperature rising events are mostly faced. Monsoon storms, and a decrease in temperature, pre-/post-monsoon storm events are experienced by more than 50 percent of farmers. Eighty-five farmers incurred significant loss amounting to BDT 14,570.00 per acre of land, for a given crop season because of sudden rainfall or flood and drought condition. Pre/post-monsoon storm, increase or decrease in temperature, and falls in the groundwater level, were identified as subsequent problems leading to reduced yield. Groundwater scarcity even increases the severity of production loss for all rice crop varieties in the country (Islam et al., 2017). Loss in agricultural yield is accompanied by several resultant impacts such as an increase in crop diseases, pest attacks, extinction of beneficiary pests, and reduction in fish production in field-adjacent water sources. Figure 4 shows the percentage distribution of farms facing these impacts of climate change and the constraints to using climate-resilient technologies. Pest attacks and crop disease are the major problems experienced in the study regions. Around 53 percent of farmers reported the 'extinction of beneficiary pests' problem and a small proportion (12.63%) also reported the 'reduction in fish catch problem' from adjacent water bodies. The most-reported constraints to using conventional climate-resilient technologies include the unavailability of climate change updates or forecasts, higher cost of installing a water-saving irrigation system, limited knowledge about the benefits of a regular soil test, an inadequate supply of climate-resilient seeds, and difficult access to training on climate-resilient technologies. It may be that farmers are not aware of climate-friendly clean energy sources such as solar power systems. Farmers rarely demand, purchase or install solar power in their fields. This may keep solar power less familiar and increase climate-depleting energy usage in agriculture.

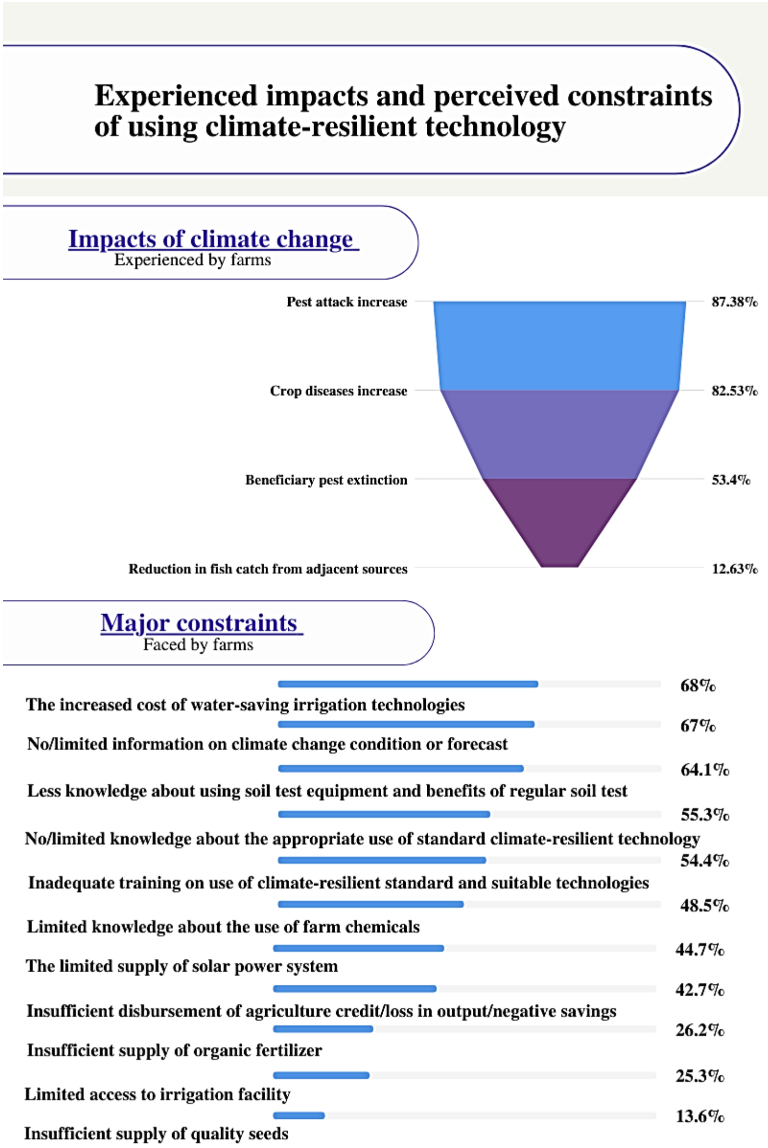

Figure 4: Experienced impacts in cropping and constraints of using climate-resilient technology
Source: Field survey

Table 4 Pattern of climate change (CC) and loss in yield

Climate change conditions	Numbers of farms facing	Loss in yield (price in Taka per acre_ per crop season)	Numbers of farms that recognised the responsible CC condition)
Sudden rainfall	103	14,570	85 (3.24)
Flood/drought	103		
Temp rising	88	11,275	57 (2.42)
Temp decreasing	68		
Pre/post-monsoon storm	63	11,950	56 (1.96)
Monsoon storm	76		
Fall in groundwater level	99	8,740	75 (2.56)

Note: Likert opinion-point averages are shown in the parentheses. A five-point scale is considered where condition intensity grows along with the scale points.
Source: Field survey

4.2.2 Environmental impacts of agriculture and ESA practices

Chemical-based agriculture often imposes negative impacts on the farm environment (Sabiha et al., 2016). Table 5 shows the number of post-harvest environmental impacts. These include a reduction in soil water holding capacity, soil hardness, and a reduction in soil fertility. Based on the Likert scale, water pollution (4.12) is the most reported problem. To minimize the damage to the farm environment as well as limit the possible future loss during the next cropping period, farmers resort to alternative methods of cultivation. They are operationalized in this study as ESA practices. The categories are biological, physical, environment-safe chemical, cultural/local, corrective, and preventive methods (Figure 5). Local/cultural and biological control methods are the most adopted ESA practices that also have on-farm protective and controlling impacts on the environment. This has an important implication for both local resource conservation and climate-resilient agriculture. In the category of local/cultural methods, most farmers use organic fertilizers to deal with soil-related problems directly and water-related problems indirectly. It is also observed that any type of soil management including structure, nutrition, and toxicity control is the most preferred option for ESA practices.

Table 5 Post-harvest environmental impacts

Impact names	Number of farms	Impact names	Number of farms
fertility reduction	90 (2.46)	soil salinity	22 (2.41)
soil toxicity	35 (2.98)	skin problem	67 (2.43)
soil water holding capacity	94 (2.88)	waterlogging	31 (2.74)
soil erosion	41 (1.78)	water pollution	55 (4.12)
soil hardness	60 (2.13)	fish catch reduction	60 (3.01)

Note: Likert opinion-point averages are shown in the parentheses. A five-point scale is considered where impact intensity grows along with the scale points.
Source: Field survey

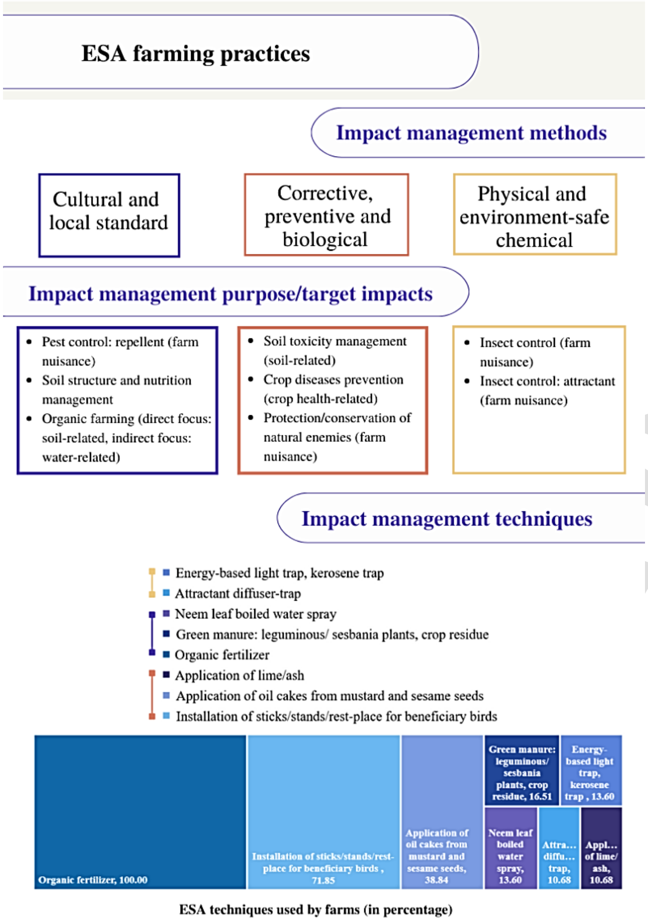

Figure 5: Management methods, impacts and techniques of ESA farming technology
Note: Similar line colour of shapes is used for each method and the respective management techniques.
Source: Field survey

4.3 Path analysis and structural model results

Table 6 and Figure 6 present the direct effects of parameters in path analysis including the hypotheses testing results. Concerning the TPB framework, an expected sign is observed in eight relationships including the *intention* to *behaviour* relationship. Results show that farms with a high index value of environmental impacts have a low index value of ESA adoption (-0.21). It was observed in the study area that there are multiple adverse post-harvest on-farm environmental impacts (Table 5). The finding also explains the causal relationships between exogenous variables on the *intention* variable, i.e., the EII. It is found that there is an inverse relationship between the index of benefit from ESA practice (-0.44) and after-harvest on-farm environmental impact (EII). The *attitude* component in the TPB framework is significant in this respect because it validates the proposed ESA approach. It implies that if farmers perceive the benefits of ESA, they intend to reduce environmental impacts and will employ ESA methods. The index of climate change condition (0.33) and chemical fertilizer use (0.03) are related directly to the EII. This result supports the findings of the existing studies on increasing pest attack, crop disease, and yield loss that are a consequence of temperature increase and variable rainfall and impacts of farm chemicals usage (Rosenzweig et al., 2001; Valdivia et al., 2010). The education level of farmers, farming experience, and the share of agricultural income contribute to limiting farm-land environmental consequences. This could contribute to ESA diffusion as well. In previous studies, education has a significant effect on influencing both intention and behaviour (Daxini et al., 2019; Lin and Wang, 2021). The use of organic fertilizer (0.07) could not exert substantial influence on EII implying its lower usage. The SEM analysis also shows a direct relationship between the index of constraints using ESA practices and EII and partly explains why the adoption of ESA techniques is low in the study area. This exhibits the largest effect (1.45) on the on-farm environmental impact among all the exogenous variables. Relevantly, multiple resource constraints and less adaptive capacity of farmers are observed in the study area. This finding is consistent with Alauddin and Sarker (2014). The authors observed that finance and information including prior climate information are the major barriers to farmers' adaptation. Similarly, they are observed as decreasing factors for any water-saving technology adoption, in Alauddin et al. (2020).

Table 6: Path analysis results and TPB hypotheses testing

***Intention* (Impact on EII)**		
Variables	**Coefficients**	**The expected sign of a relationship in TPB (Yes/No/Reject)**
IEB	-0.44***	Yes
ICCN	0.33**	Yes
IHP	-0.77	Reject
Education	-0.26*	Yes
Farming experience	-0.17**	Yes
Access to extension service	2.81*	No
Subsistence pressure	1.74	Reject
Agricultural income	-11.89***	Yes
Land ownership	2.88	Reject
Organic fertilizer use	0.07**	No
Chemical fertilizer use	0.03**	Yes
ICE	1.45***	Yes
***Intention* → *Behaviour* (Impact on IEP)**		
EII	-0.21***	Yes
Model Fit		
Chi-square ratio	495.36***	
R^2	0.85	

Note: ****p*< 0.01, ***p*<0.05, **p*< 0.10
Source: Field survey

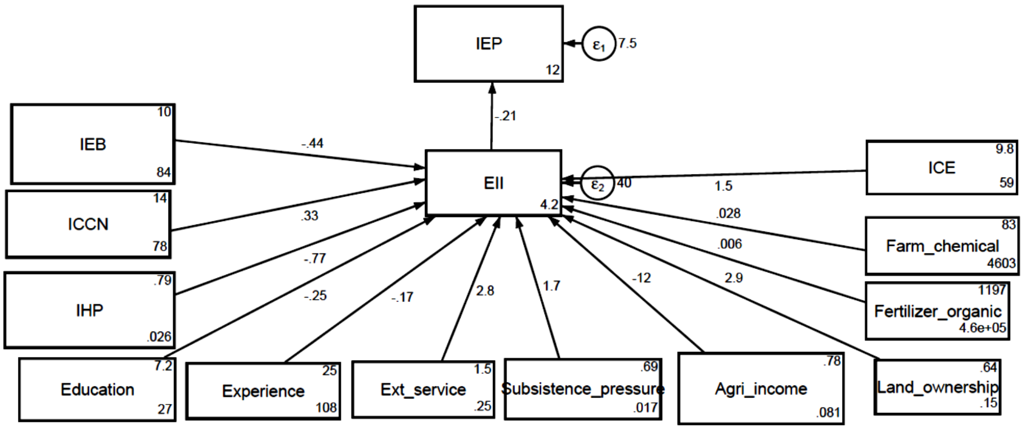

Figure 6: SEM path analysis of EII and IEP

5. Conclusion

This study proposes an integrated approach to environment-smart agriculture (ESA) that determines the climate resilience potential of a farm. A composite index of environment-smart agricultural practices (IEP) is formulated as a measure of that resilient potential. The IEP focuses on five mostly-affected target areas of farm environment and climate and comprises biological, physical, local, preventive and corrective management techniques. The TPB theoretical framework is used to validate the IEP index. This study evaluates how farmers' attitudes (i.e., IEB), subjective norms (i.e., ICCN), and perceived behavioural control (e.g., the ICE, experience, and education) together shape their intentions (of limiting EII) and actual behaviour (adopting the ESA). Structural equation modelling and path analysis were employed to test these linkages on a sample of 103 farms in north-western Bangladesh. The important observations from the path analysis are: (i) farms having a higher index of on-farm environmental impacts (EII) hold a lower value of the IEP, implying the potential advantages of the ESA practices, (ii) farmers who have better knowledge about the advantages of the ESA are less likely to experience negative impacts from cultivation on their farm environment, and (iii) farms that suffer from a higher level of climate change (ICCN) influence the environmental impact of agriculture adversely. Thus, farms that face more constraints to the use of ESA practices are most likely to generate a higher level of environmental impacts.

The path analysis provides a comprehensive assessment of the proposed approach to ESA practices. Therefore, wider-scale execution of the ESA practices not only helps to manage post-harvest environmental impacts but also increases the climate-resilience potential of a farm. Since ESA practices mostly comprise local scale measures, they are cost-effective and do not require external funds. This is a significant indication of promoting ESA in the bottom-up policy framework. We suggest that i) information and knowledge diffusion on ESA should be undertaken by local agricultural extension wings with a focus on local traditional measures and spatial heterogeneity, ii) government mitigation and adaptation projects should include economic incentives on local climate-resilient technology, and iii) training on ESA and sharing the experiences of farmers who already adopted ESA would increase its adoption and social capital. Furthermore, the theoretical framework and findings could be utilized in future inquiries. ESA framework is tested in this study addressing local climate hazards and its mitigation pathways. However, ESA practices as well as perception towards them, may vary spatially with climate disaster type, the intensity of impacts, other idiosyncratic shocks and their coping mechanism. Thus, it would be useful for future research to capture the regional effect in ESA adoption and address the heterogeneity in local and traditional ESA options.

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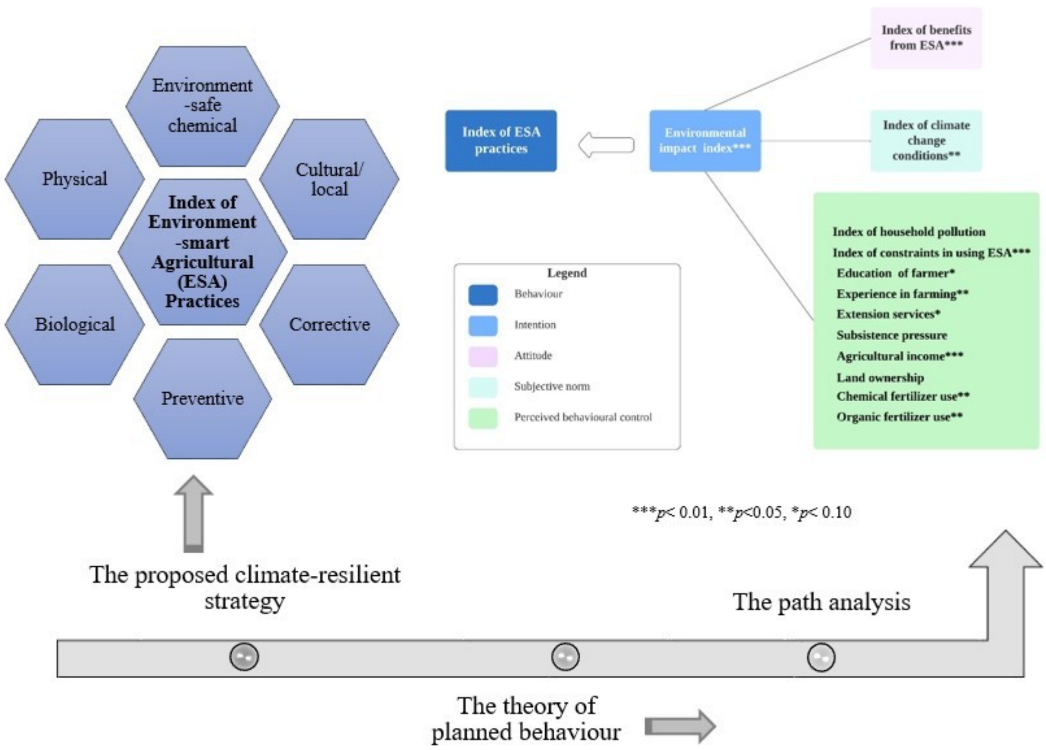
Integrated environment-smart agricultural practices: A strategy towards climate-resilient agriculture

Research highlights:

- Environment-smart agriculture (ESA) is evaluated.
- An integrated framework is proposed to construct an index of ESA practices (IEP).
- The linkage between the ESA index and climate-resilient farming is verified.
- The importance of ESA in the bottom-up policy framework is observed.

Graphical Abstract



Integrated environment-smart agricultural practices: A strategy towards climate-resilient agriculture

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