

Evaluation of Low-Carbon Sustainable Technologies in Agriculture Sector through Grey Ordinal Priority Approach

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Abstract: The agriculture sector plays a vital role in the economy, society, and environment, the three dimensions of sustainability. The agriculture sector contributes 12% to 14% of global greenhouse gas (GHG) emissions to the atmosphere, negatively impacting climate change. Using low-carbon and sustainable agricultural technologies can help mitigate climate change and global food security issues. But selecting and prioritizing the best technologies among all alternatives has always been an issue for decision-makers because of various uncertainty related to the agricultural sector. Therefore, the current study intends to identify and prioritize the key low-carbon and sustainable agricultural technologies. The current study makes a pioneering attempt in employing the Grey Ordinal Priority Approach (OPA-G), a modern multi-attribute decision-making technique, for the evaluation of low-carbon and sustainable technologies for the agricultural sector.

Keywords: Low-carbon; agricultural technology; grey system theory; multiple criteria decision making; grey ordinal priority approach; sustainable development

1. Introduction

Reducing emissions from agricultural activities is a global issue getting exceeding attention these days. For minimizing the carbon emissions from the agriculture sector, the role of low carbon technologies is hard to ignore. The agriculture-related activities produce emissions that negatively affect the environment. These emissions are usually associated with livestock, burning of crop residues, using N fertilizer, agricultural soil, enteric fermentation, biomass burning, deforestation etc. (Khan, 2020). Studies have argued that sustainable agricultural technologies can play an essential role in achieving low carbon agriculture plans (Vinholis *et al.*, 2021) and ensuring green food production for resource conservation (Zaman, 2020). Unlike the emissions from other energy-intensive economic sectors, the agriculture sector's greenhouse gas emissions are usually underestimated (McMahon, 2019). Agriculture-related activity directly contributes 12%-14% of global greenhouse gas (GHG) emissions to the atmosphere (Beach *et al.*, 2008; Tian *et al.*, 2011). China, India, Brazil, and the USA are the biggest emitter of GHG from the agricultural sector. Agricultural activity in other developing countries is also growing at a fast pace (Bennetzen *et al.*, 2016), indicating greater emissions in the future. The current study recognizes this fact and tries to highlight the issue of greenhouse gas emissions from the agriculture sector and its implications for sustainable development and food security issues. Notably,

low-carbon and sustainable agricultural technologies can help agricultural sectors of different countries reduce emissions.

It is always difficult to select suitable technologies for the agricultural industry (Ren *et al.*, 2017). Hence, considering sustainable criteria such as economic, social, and environmental, it has become even more difficult for the decision-makers to select the best low-carbon and sustainable technologies for the agricultural industry. However, multiple criteria decision-making (MCDM) is a popular technique to identify the best alternative among all possible alternatives based on different conflicting criteria. Thus, numerous decision-making methods have been proposed to date to solve MCDM problems. For example, Wang *et al.* (2018) used the Fuzzy AHP-VIKOR method to prioritize sustainable energy technology for the agricultural sector. Yu *et al.* (2019), Memari *et al.* (2019), and Li *et al.* (2019) applied the TOPSIS method for selecting the best suppliers for different industries. Amindoust (2018) and Ghadimi *et al.* (2018) used a fuzzy inference system to deal with the uncertainty in supplier selection. These studies proved the wide acceptance of MCDM methods among scholars. However, considering the variety of applications in decision-making methods, it is observed that there are many limitations in existing MCDM models (Mahmoudi *et al.*, 2020). Javed *et al.* (2020) classified uncertainty in MCDM methods into five classes, as shown in Figure 1.

In light of the above discussion, the current study attempts to find a reliable solution for the decision-makers so that they can select the best possible alternatives based on different criteria. The present study uses the Grey Ordinal Priority Approach (OPA-G), a modern multi-attribute decision-making technique, to evaluate low-carbon and sustainable agricultural technologies while dealing with most of the problems mentioned above.

The rest of the study is organized as follows. Section two describes the reviews of literature related to the role of agriculture in sustainable development goals (SDGs), finds the primary sources of emissions from the agricultural sector, and identified the critical low-carbon and sustainable agriculture technology that can play an important role in mitigating climate change and provide global food security. Grey Ordinal Priority Approach (OPA-G) model is also explained. Section three develops the Grey Ordinal priority approach (OPA-G), a modern multi-attribute decision-making model that will help evaluate low-carbon and sustainable agricultural technologies. Section four describes the result and discussion of the OPA-G model, and finally, the study will conclude with essential suggestions and implications for the countries where agriculture plays a vital role in the economy and maintaining food security.

2. Literature Review

2.1 Role of Agriculture Sector in Sustainable Development

The concept of sustainable development (SD) is relatively new, but, today it is one of the most widely discussed topics worldwide. According to the United Nations Brundtland Commission Report (1987), it is the "development that meets the needs of the present without compromising the ability of future generations to meet their own needs." The agriculture sector is a key sector contributing to sustainable development (Smith *et al.*, 2014). According to FAO (2020.), among 17 sustainable development goals (SDGs) promoted by the United Nations, SDG1, SDG2, and SDG13 are directly linked to the Agricultural sector. To achieve sustainability in the agricultural sector, it must meet the present and future generations' needs by ensuring all the sustainability dimensions (economic, social and environmental) (FAO, 2021). But climate change poses the biggest threat to the agricultural sector; global agricultural production and food security already has been compromised due to climate change (IPCC, 2012). Growing evidence indicates that Climate change, agriculture, and global food security are closely linked to each other (Huo & Huo., 2019; Ray *et al.*, 2015; Hatfield *et al.*, 2014; Wheeler & Braun, 2013; Olesen *et al.*, 2011). It is important to note that agricultural production also has a negative impact on the environment, e.g., various agricultural activities such as tillage, livestock, burning of crop residues, using N fertilizer, agricultural soil, enteric fermentation, biomass burning, deforestation etc. release a huge amount of anthropogenic greenhouse gas (GHG) to the atmosphere (Li *et al.*, 2021; Vetter *et al.*, 2017). They have also argued that adopting low carbon and sustainable agricultural technology can help mitigate climate change and achieve sustainable development.

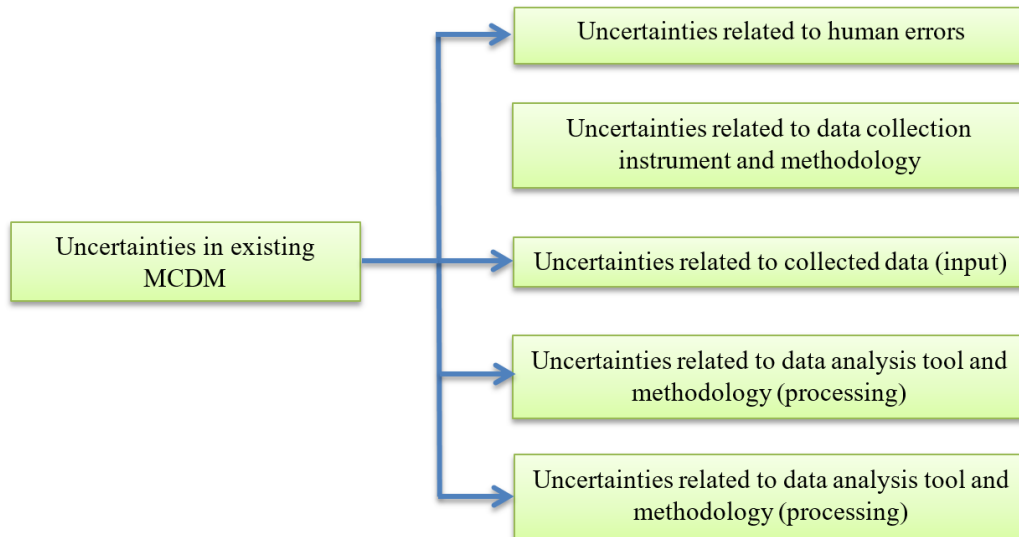


Figure 1. Five-dimensional uncertainties in MCDM methods (Source: Javed *et al.*, 2020)

2.2 Overview of Greenhouse Gases Emissions from Agriculture Sector

Agricultural activities directly contribute greenhouse gas (GHG) emissions to the atmosphere (Beach *et al.*, 2008; Tian *et al.*, 2011). Paustian *et al.* (2016) highlighted that 10% – 14% of global GHG emissions are related to agricultural production. A study by World Resources Institute has argued that the agricultural sector is the world's second-largest GHG emitter, after the energy sector, and this trend is less likely to change in the future (Russell, 2014). Unless taking any action to mitigate climate change, GHG emissions from the agricultural sector will reach 58% by 2050 (Arcipowska *et al.*, 2019). However, currently, GHS emissions from the agriculture sector are estimated at approximately 60% from Africa and Latin America, 30% from Asia, and 10% from Europe and North America (Anuga *et al.*, 2020). Considering the last twenty years, 1996 – 2016, China, India, the USA, and Brazil were the most responsible countries for GHG emissions from the agricultural sector. 37% of global agricultural GHG emission comes from these four countries (Arcipowska *et al.*, 2019). Similarly, agricultural GHG emissions in other regions such as Africa also rises dramatically in the last 20 years. Average annual GHG emissions from the agriculture sector increase between 2.9% to 3.1%, while in China and India, it has increased by 16% and 14%, respectively. Meanwhile, Australia, Argentina, and Brazil are the top three countries for agricultural emission in terms of per capita (Tongwane & Moeletsi, 2018). Many studies have documented that the primary sources of GHG emissions from the agricultural sector are livestock, burning of crop residues, use of N fertilizer, enteric fermentation, biomass burning, deforestation etc. (Lybbert & Sumner, 2012; Khan *et al.*, 2020; EU, 2020). See Figure 2 for details. Moreover, many researchers have pointed that there is a tremendous opportunity to mitigate a substantial amount of GHG from the agriculture sector through changes in agricultural management practice in different regions around the world; China (Li *et al.*, 2021; Huo & Huo, 2019), India (Pathak *et al.*, 2012), Brazil (Vinholis *et al.*, 2021), Europe (EU, 2020), France (Meynard *et al.*, 2018), Sub-Saharan Africa (Powlson *et al.*, 2016), South America (De *et al.*, 2017), these changes are closely related to low-carbon and sustainable agriculture technologies which can help the agricultural sector to mitigate climate change by reducing GHG emission and drive towards global food security and sustainable development.

2.3 Causes of CO₂ Emissions from Agriculture Sector

Like other industries, the agricultural sector is also responsible for producing a huge amount of carbon dioxide (CO₂). Several studies have been executed to find the leading causes of CO₂ emission from the agricultural sector. Agricultural management practices, such as tillage, residues management,

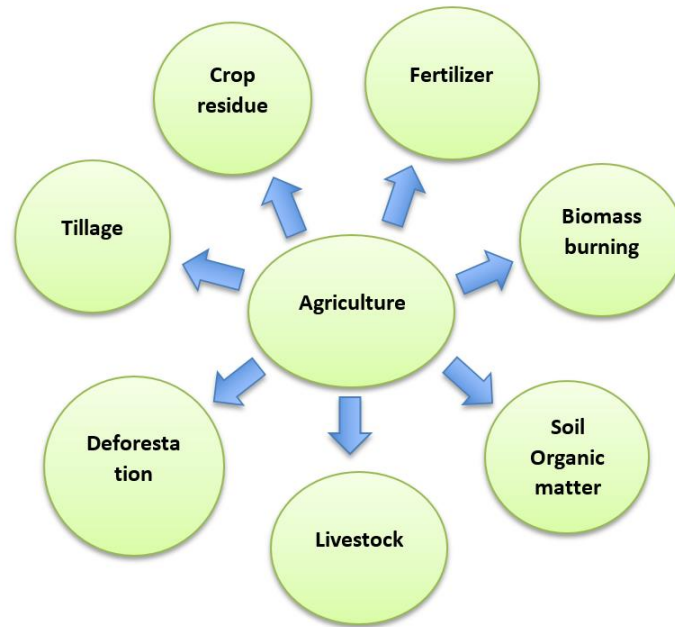


Figure 2. Primary sources of carbon emission from the agricultural sector

fertilizer management, are the key sources of CO₂ fluxes from agriculture to the atmosphere (Khan *et al.*, 2020; Sikora *et al.*, 2020). The use of fossil fuel in different agricultural operations, manufacturing of fertilizer, and pesticides are also responsible for producing CO₂ (Bhatia *et al.*, 2012; Redman *et al.*, 2020). Soil is the largest pool of CO₂, storing about 2344PgC of soil organic carbon SOC (Jobbágy & Jackson., 2000). There is considerable evidence in the literature that confirms that conventional tillage system release protected SOC by disturbance and disruption of the soil, causing the soil to release a substantial amount of CO₂ into the atmosphere (Dimassi *et al.*, 2014; Luo *et al.*, 2010; Ussiri & Lal, 2009; Six *et al.*, 2004). Abdalla *et al.* (2016) have argued that soil management (especially tillage systems) plays a crucial role in CO₂ emission from agriculture. Using a Meta-Analysis, they have observed that a no-tillage system can reduce up to 21% of CO₂ emissions than the conventional tillage system, which can significantly help mitigate climate change. However, not only tillage system contributes CO₂ emission to the atmosphere, but leftover material from agriculture (crop residues) also contains a high amount of CO₂ (Cardoen *et al.*, 2015). Considering ten years from 2003 to 2013, Cherubin *et al.* (2018) documented that the world has produced 3830 million metric tons (MT) of crop residues from agriculture. Deshavath *et al.* (2019) reported that in 2016 alone top four agricultural production countries – China, India, the USA, and Brazil – have burnt 181.8 MT of crop residues in open fields, contributing 15.8 MT of CO₂ emission to the earth's atmosphere. It is happening not because of farmer's unawareness of the environmental impact of open burning of crop residues but because of a lack of idea and information about low-carbon and cost-effective technologies (Kumar & Singh, 2021). Prasad *et al.* (2020) argued that crop residues have tremendous potential for producing renewable energy. Using the Life cycle assessment (LCA) method, they have shown that proper utilization of crop residues can play a vital role in cutting down net CO₂ emissions and reducing the climate footprint from agriculture.

2.4 Identification of Low-Carbon Sustainable Technologies in the Agriculture Sector

Many studies have tried to identify and evaluate low carbon and sustainable agricultural technologies. Table 1 summarizes the literature on low carbon and sustainable agricultural technologies' evaluation. Based on the review of literature, the current study identified the following low carbon and sustainable agricultural technologies for potential evaluation:

Table 1. Summary of literature on low carbon and sustainable agricultural technologies' evaluation

Year	Description	Country of focus	Evaluation technique	Reference
2012	The study identified six low carbon technologies	India	Scenario-based analysis	Pathak <i>et al.</i> (2012)
2016	The study identified Conservation Agriculture as a critical sustainable agricultural technology for the mitigation potential of climate change and food security	Sub-Saharan Africa	Meta-analysis	Powelson <i>et al.</i> (2016)
2015	The study identified integrated soil fertility management (ISFM) as a key technology for increasing food security and GHG mitigation potential	N/A	N/A	Roobroeck <i>et al.</i> (2015)
2015	The study identified 6 agricultural technologies with great mitigation potential	China	Bottom-up assessment	Lybbert and Sumner (2012)
2016	The study identified a No-tillage system as a key agricultural technology for reducing CO ₂ emissions	N/A	Meta-analysis	Abdualla <i>et al.</i> (2016)
2017	The study identified six low carbon technology (RDPLi, NT, ICLFS, BNF, PCFF, IAW)	South America	Scenario-based analysis	De <i>et al.</i> (2017)
2017	This study identified 9 low carbon and sustainable agricultural technology	N/A	Qualitative approach	Uppala <i>et al.</i> (2016)
2018	The study identified Crop diversification as a key sustainable agricultural technology	France	Threefold approach	Meynard <i>et al.</i> (2018)
2019	The study identified two sustainable agricultural technology-based different criteria	China	A fuzzy AHP-VIKOR	Wang <i>et al.</i> (2019)
2019	The study identified one sustainable agricultural technology (SRI)	Mali	Qualitative approach	Mwalupaso <i>et al.</i> (2019)
2020	The study identified Agroforestry as an important agricultural technology for food security, increasing resilience, and mitigating climate change	Southern Malawi	Double hurdle specification with a control function approach	Amadu <i>et al.</i> (2020)
2020	The study identified five low carbon technology	Africa	Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach.	Anuga <i>et al.</i> (2020)
2020	The study identified ten low carbon technologies	China	Theory of Planned Behavior	Li <i>et al.</i> (2020)
2020	The study identified crop rotation as a sustainable agricultural technology based on different criteria	India	AHP-GIS	Singha <i>et al.</i> (2020)
2020	The study identified SWC and WH as important sustainable agricultural technology.	Ethiopia	Qualitative approach	Yaekob <i>et al.</i> (2020)
2020	The study identified ICLS and ICLFS as a viable low carbon technology	Brazil	Econometric regression models	Vinholis <i>et al.</i> (2021)
2021	The current study identifies (and prioritizes, based on selected criteria) nine low carbon agricultural technology, e.g., ICLS, ICLFS, No-tillage, CS, etc.	N/A	Grey Ordinal Priority Approach (OPA-G)	The current study

*ICLS: Integrated Crop Livestock System; ICLFS: Integrated Crop-Livestock System; CS: Carbon Sequestration; SWC: Soil and Water Conservation; WH: water harvesting

2.4.1 Integrated crop-livestock systems (T1). Integrated crop-livestock systems (ICLS) are diversified agricultural production systems that can enhance food production and contribute to sustainable intensification while improving environmental quality by reducing net GHG emissions (Morales *et al.*, 2019). ICLS advances ecological interaction between different natural resources such as (crops, animals, and grassland) and reduces the need for chemical fertilizers and other inputs by developing organic fertilization from livestock waste (Hendrickson *et al.*, 2008). This low-carbon and sustainable technology are very important for sustainability, increasing profitability, and economic stability (Russelle *et al.*, 2007). However, despite economic, social, and environmental benefits, farmers' workload becomes a significant concern for this technology (Moraine *et al.*, 2014).

2.4.2 No-tillage (T2). The no-tillage system is an agriculture technique that helps mitigate CO₂ emissions from dry land by avoiding soil disturbance, reports Abdalla *et al.* (2016). Their study finds that conventional tillage system emits 21% more CO₂ than No-tillage system. It is a popular agricultural technology worldwide because of its ability to maximize soil water infiltration, reduce soil erosion, and increase organic carbon stock (Page *et al.*, 2019). However, Powlson *et al.* (2014) focused on its benefits and limitations. They suggested this low carbon agricultural technology significantly impacts soil properties, crop growth, and the environment. These technologies' key benefits are; increased rainfall infiltration, Increased soil biological activity, Increased crop yields, decreased risk of soil erosion, labor/time saved through avoiding tillage operations, reduced costs, and CO₂ emission by elimination of fossil fuel use in tillage operations. However, despite many benefits, they have also argued that this technology has some limitations in the long term. For example, crop yields may remain unchanged in some situation, nitrous oxide emissions may increase, extra labor force for weed control may be needed, in wet climates planting crops may be delayed, machinery for planting crops may not be available in less developed countries, and farm income may not increase in near term.

2.4.3 Integrated crop-livestock-forest system (T3). According to Vinhols *et al.* (2020), an integrated crop-livestock-forest system (CLFS) is an agro-ecosystem management practice that can improve the soil's biological, chemical, and physical conditions. This low carbon agricultural technique combines different farming systems such as crop-forest, crop-livestock, forest-livestock, and crop-livestock-forest (Valani *et al.* 2021). This technology's benefit includes increasing cycling and nutrient utilization efficiency, reducing production costs, and protecting climate change by reducing GHG emissions.

2.4.4 Conservation agriculture (T4). Conservation agriculture (CA) technology is considered a greener solution for mitigating negative impacts from the agricultural sector (Gilbert, 2012). It is a potential cropping system that can minimize the adverse effects of declining soil fertility and minimize environmental degradation (Kassam *et al.*, 2009). This modern agricultural technique can enable farmers in different parts of the world to achieve sustainable agricultural production (Hobbs *et al.* 2008). Large-scale farmers located in various regions such as North America, South America, Australia, New Zealand are benefiting by adopting CA technology (Kassam *et al.*, 2009). Despite many complementariness, there are some constraints and challenges for adopting CA technology, especially in small-scale farming linked to limited resources such as land, labor, capital etc. (Valbuena *et al.*, 2012). However, its advantages outweigh its limitations.

2.4.5 Integrated Soil Fertility Management (T5). Integrated Soil Fertility Management (ISFM) is considered a means of enhancing crop productivity and maximizing agronomic inputs' efficiency, thus contributing to sustainable intensification (Vanlauwe *et al.*, 2015). ISFM is climate-smart agriculture (CSA) practices associated with cropping, fertilizers, organic resources, and other processes in addition to increasing agricultural production and input use efficiency. In the long run, ISFM provides productivity gains, increased resilience, and mitigation benefits (Roobroeck *et al.*, 2015). Despite the usefulness of ISFM for food security, farmers' income and environmental protection lack of awareness and disbeliefs about ISFM become a significant concern for adopting this low-carbon and sustainable agricultural technology (Lambrecht *et al.* 2016).

2.4.6 Agroforestry (T6). The concept of agroforestry is an association of trees with crops or livestock on the same land that embraces a broad range of systems under different management schemes (Martin

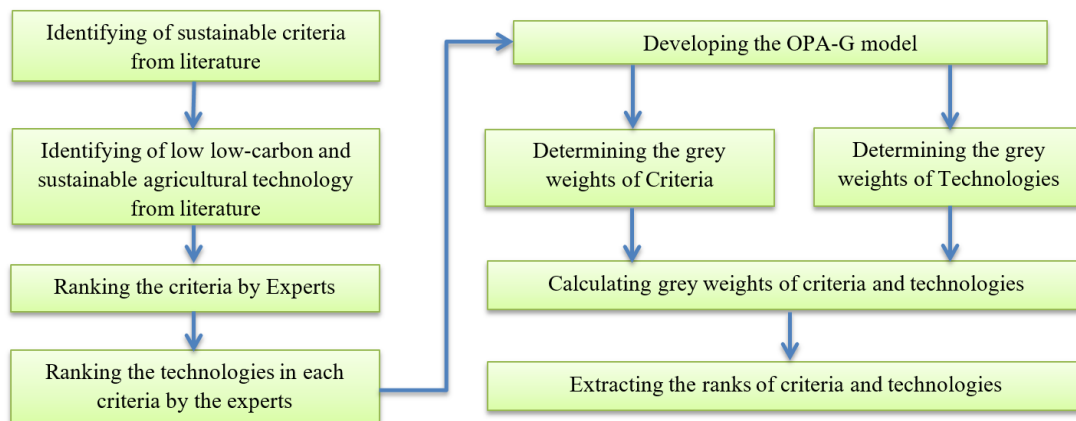


Figure 3. The framework of the study

et al., 2019), which can provide many benefits, including increase crop yields, reduce soil erosion, conserving biodiversity and increasing soil fertility (Nair *et al.* 2010; 2009). De Stefano and Jacobson (2018) argued that agroforestry could be a viable opportunity to tackle the climate change issues, reducing CO₂ emissions from the agricultural sector. Considering all these benefits, Waldron *et al.* (2017) argued that agroforestry could help to increase global food security and, in the meantime, can help to achieve SDGs.

2.4.7 Carbon sequestration (T7). Carbon sequestration is the process of balancing carbon dioxide into an atmospheric C pool. Carbon sequestering in the agricultural sector requires a change in agricultural management practices such as pesticide use, irrigation, and machinery (West & Marland, 2002). This technology has a considerable potential to reduce CO₂ emissions from the agriculture sector and fossil fuel emissions (Schlesinger, 1999). This process gains enormous attention as an alternate way to help stem the rate of greenhouse gas growth and associated changes in our climate. Scientist prioritizes carbon sequestration as the primary goal with ancillary improvements in water management, soil erosion, and food security.

2.4.8 Crop diversification (T8). The agricultural sector is the most sensitive to the climate change issue. Studies have documented a direct link to climate change and agricultural production, more likely negative impacts than positive (Li *et al.*, 2021; Huo & Huo, 2019; BIRTHAL & Hazrana, 2019). Crop diversification has a great potentiality to increase the sustainability of arable farming systems that minimize the inputs of (irrigation water, fertilizers, pesticides) expanding the heterogeneity of habitat mosaics, or reducing yield gap associated with too frequent returns of the same species (Meynard *et al.*, 2018). BIRTHAL and Hazrana (2019) have found that crop diversification has many benefits in the long run. On the other hand, Magrini *et al.* (2016) and Lithourgidis *et al.* (2011) argued that historically established to support large-scale specialization, selection of appropriate crops, and short-term maximization of profits with chemical inputs are the main barriers to the adaption of this technology.

2.4.9 Soil and water conservation (T9). Soil and water conservation (SWC) is a sustainable agriculture management system that reduces soil erosion, increases agricultural production yield, and grows organic carbon stock (Mekonnen, 2020; Adimassu *et al.*, 2017). However, different scholars have shown that the impact of SWC technology has inconsistent results on crop yield and economic profitability in the short-run (Kato *et al.*, 2011; Kassie *et al.*, 2011). As a result, farmer's adaption rate to this technology is meagre. Asfaw *et al.* (2017) pointed out that inadequate information, poor skills, and inadequate transportation and communication are responsible for this technology's low adaption, especially in developing countries.

2.5 Grey Ordinal Priority Approach

2.5.1 Grey system theory. Deng Julong introduced the Grey System Theory in 1982 (Ju-Long, 1982) where a white–grey–black spectrum is used to explain the uncertainty of a system (Hao *et al.*, 2006). Grey System Theory has a wide range of popularity among researchers from different fields because of its applicability to solve real-world situations where incomplete information and uncertainty exist. The key areas of Grey System Theory include grey relational analysis, grey generating space, grey forecasting, grey decision making, grey control, and grey mathematics. Grey System Theory has seen application in numerous fields, including agriculture (Tan *et al.*, 2014), supplier selection (Mahmoudi *et al.*, 2021a), economic growth analysis (Huang *et al.*, 2020), health care management (Aydemir & Sahin, 2019; Javed and Liu., 2018), sustainable development (Ikram *et al.*, 2021; Abid *et al.*, 2021), environment (Hao *et al.*, 2006), electromagnetic data processing (Jiang *et al.*, 2017), traffic flow prediction (Xiao *et al.*, 2020), energy and emissions (Chen *et al.*, 2021; Zhu *et al.*, 2019), project management (Sheikh *et al.*, 2019; Javed & Liu, 2019), machine learning (Xie *et al.*, 2021; Ma, 2019), among others. It can be seen that the application of Grey System Theory is widespread and multi-disciplinary. Some researchers even argued its superiority over other methods such as fuzzy set theory, considering the ability and flexibility of dealing with ambiguity and uncertainty, independence over membership function, and ability to handle a small sample size (Chithambaranathan *et al.*, 2015; Ng and Deng, 1995). Grey Ordinal Priority Approach is a new multi-criteria decision-making technique that fuses the advantages of grey system theory with the Ordinal Priority Approach (OPA) and is discussed in the subsequent section.

2.5.2 Grey Ordinal Priority Approach. The ordinal priority approach (OPA) is an emerging multi-criteria decision-making (MCDM) technique developed by Ataie *et al.* (2020) and has recently seen some extensions. They argued that this model has a strong capability of supporting both single and group decision-making. Also, it can calculate the weights for different experts, criteria, and alternatives simultaneously, while most other MCDM models only can produce a ranking of alternatives based on the expert's opinion. The recent literature has demonstrated the OPA's effectiveness with interesting results. For example, Mahmoudi *et al.* (2020a) showed the suitability of the OPA-based framework for problems involving big data. Mahmoudi *et al.* (2021b) proposed the Fuzzy Ordinal Priority Approach to solve the decision-making problems through linguistic information.

Grey Ordinal Priority Approach (OPA-G) is another important member of the OPA family and was proposed by Mahmoudi *et al.* (2021a). They demonstrated its effectiveness in solving sustainable supplier selection problems. They have shown that OPA-G can work without any linguistic variable or pairwise comparison-based data and have a high capability of dealing with greyness/uncertainty. While considering the ordinal priorities, the OPA-G model can provide the weights for experts, criteria, and alternatives. Table 2 shows the explanation of sets, indexes, variables, and the parameters of the OPA-G model (Mahmoudi *et al.*, 2021a).

Table 2. Sets, indexes, variables, and parameters of the OPA-G model

sets	
I	Set of experts $\forall i \in I$
J	Set of criteria $\forall j \in J$
K	Set of alternatives $\forall k \in K$
Indexes	
i	Index of the experts $(1, \dots, p)$
j	Index of preference of the criteria $(1, \dots, n)$
k	Index of the alternatives $(1, \dots, m)$
Variables	
$\otimes Z$	Grey objective function
$\otimes W_{ijk^r}$	Grey weight (importance) of k^{th} alternative based on j^{th} criterion by i^{th} expert at r^{th} rank
Parameters	
$\otimes i$	Grey rank of the expert i
$\otimes j$	Grey rank of the criterion j
$\otimes r$	Grey rank of the alternative k

Table 3. The demographic profile of the respondents

Gender	Male (70%) Female (30%)
Age	More than 50 years old (20%) 41 – 50 years old (30%) 31 – 40 years old (20%) 21 – 30 years old (30%)
Industry	Agriculture, Forestry and Other Land Use (80%) Other (20%)
Position/post	Top level manager (40%) Middle level manager (40%) Junior level manager (20%)
Work Experience	More than 12 years (40%) 9 - 12 years (20%) 7 – 9 years (10%) years 4 – 6 years (20%) 1 – 3 years (10 %)
Organization type	Public (50%) Private (50%)
Total sample	10

Understanding of some definitions is mandatory before the computational steps of the OPA-G are discussed. These definitions are defined below and are adapted from Mahmoudi *et al.* (2020).

Definition I: Grey number $\otimes A$ is described as follows:

$$\otimes A = [\underline{A}, \overline{A}], \quad \underline{A} < \overline{A} \tag{1}$$

where, \underline{A} is the lower limit and \overline{A} is the upper limit of the grey number $\otimes A$. Here, it should be noted that a grey number should not be confused with interval. Unlike an interval, a grey number is a crisp number, and its interval merely represents greyness in the exact location of this crisp number.

Definition II: Assume that A is a crisp number. Therefore, $\otimes A$ has a grey rank $[\text{Rank}(A) - 0.5, \text{Rank}(A) + 0.5]$. Equation (2) should be utilized to convert crisp rank n to grey rank n .

$$\text{Rank } \otimes n[n - 0.5, n + 0.5] \tag{2}$$

Definition III: Assume that the expert(s) is not confident about in a choice of two ranks x and y for a criterion or an alternative while $x < y$. Then, Eq. (3) should be utilized for the grey rank:

$$\text{Rank}(\otimes x, \otimes y) = [\text{Rank}(x) - 0.5, \text{Rank}(y) + 0.5] \tag{3}$$

The relevant computational steps of the OPA-G model are as follows (see Figure 3):

Step 1: First, the decision-makers need to determine the necessary criteria.

Step 2: The decision-makers must identify and select the relevant experts.

Step 3: The experts should give ranking to different criteria. If experts also doubt about the exact priority level for different criteria, they can utilize Definitions II and III.

Step 4: Determining the ranking for available alternatives in each criterion. In this step, experts still can use Definitions II and III to converts crisp rank into grey rank.

Step 5: After collecting all the data needed in Step 1 to Step 4 the OPA-G model should be solved using Eq. (4)

$$\text{Max } \otimes Z \tag{4}$$

S.t. $(\forall i, j, k \text{ and } r)$:

$$\otimes Z \leq \otimes i \left(\otimes j \left(r \left(\otimes W_{ijk}^r - \otimes W_{ijk}^{r+1} \right) \right) \right)$$

$$\otimes Z \leq \otimes i \otimes j \otimes m \otimes W_{ijk}^m$$

$$\sum_{i=1}^p \sum_{j=1}^n \sum_{k=1}^m \otimes W_{ijk} = [0.8, 1.2]$$

$$\otimes W_{ijk} \geq 0$$

where, $\otimes Z$ is unrestricted in sign.

To obtain the individual weights of criteria and alternatives, Eqs. (5) and (6) should be employed respectively.

$$W_j = \sum_{i=1}^p \sum_{k=1}^m W_{ijk} \quad \forall j \tag{5}$$

$$W_k = \sum_{i=1}^p \sum_{j=1}^n W_{ijk} \quad \forall k \tag{6}$$

Step 6: After getting all the weights of experts, criteria, and alternatives, the grey possibility degree should be calculated by the following matrix to extract the ranking of alternatives.

$$GP_{ij} = \begin{bmatrix} P(W_1 \leq W_1) & P(W_1 \leq W_2) & \dots & P(W_1 \leq W_k) \\ P(W_2 \leq W_1) & P(W_2 \leq W_2) & \dots & P(W_2 \leq W_k) \\ & & \ddots & \\ & & & \ddots \\ P(W_k \leq W_1) & P(W_k \leq W_2) & \dots & P(W_k \leq W_k) \end{bmatrix} \tag{7}$$

Finally, the following matrix results

$$P_{ij} = \begin{bmatrix} p_{w1p_{w1}} & p_{w1p_{w2}} & \dots & \dots & p_{w1p_{wk}} \\ p_{w2p_{w1}} & p_{w2p_{w2}} & \dots & \dots & p_{w2p_{w1}} \\ & & \ddots & & \\ & & & \ddots & \\ p_{wkp_{w1}} & p_{wkp_{w2}} & \dots & \dots & p_{wkp_{wk}} \end{bmatrix} \tag{8}$$

By summing up all the horizontal component of P_{ij} we can get the ranking for an individual alternative. The highest value will represent the best alternative for selection.

3. Research Methodology

3.1 Data Collection and Analysis

Data were collected from a designed survey where experts were selected in a random process from 10 different countries and fields. Following the sustainability approach, we identified three different criteria (Economic, Social, and Environmental) to evaluate low carbon and sustainable agricultural technologies. Then expert opinions were sought to prioritize those criteria on a 1-3 point scale where 1 represents high priority 3 represents low priority. Table 4 shows the opinion of experts regarding the evaluation of different criteria. Based on those criteria, experts were then asked to evaluate all the available alternatives/technologies on the same processes. Demographic information of the experts is available in Table 3. The data collected from them is available in Tables 5, 6, and 7. Microsoft Excel

was utilized for making tables and performing calculations, Google forms were utilized for preparing the questionnaire and then data collection. Lingo 9.0 software was utilized for building the OPA-G model and its execution.

3.2 The model

Because of the limited space, the model for one expert and three criteria is developed and shown below to introduce the readers to the model structure. In the current study, ten experts and nine criteria were involved, and the complete model was very lengthy, and thus is shown in the Appendix available at *zeonodo* (i.e., Shajedul, 2021). The key is islamislam.

$$\text{Max} = \frac{1}{2} * \bar{Z} + \frac{1}{2} * \underline{Z};$$

S. t.

!Expert 1 !Criteria 1

$$1.5 * 1.5 * 1.5 * (\underline{W}_{11}T_1 - \underline{W}_{11}T_2) \geq \bar{Z};$$

$$0.5 * 0.5 * 0.5 * (\bar{W}_{11}T_1 - \bar{W}_{11}T_2) \geq \underline{Z};$$

$$1.5 * 1.5 * 1.5 * (\underline{W}_{11}T_2 - \underline{W}_{11}T_4) \geq \bar{Z};$$

$$0.5 * 0.5 * 0.5 * (\bar{W}_{11}T_2 - \bar{W}_{11}T_4) \geq \underline{Z};$$

$$1.5 * 1.5 * 1.5 * (\underline{W}_{11}T_4 - \underline{W}_{11}T_5) \geq \bar{Z};$$

$$0.5 * 0.5 * 0.5 * (\bar{W}_{11}T_4 - \bar{W}_{11}T_5) \geq \underline{Z};$$

$$1.5 * 1.5 * 1.5 * (\underline{W}_{11}T_5 - \underline{W}_{11}T_8) \geq \bar{Z};$$

$$0.5 * 0.5 * 0.5 * (\bar{W}_{11}T_5 - \bar{W}_{11}T_8) \geq \underline{Z};$$

$$1.5 * 1.5 * 1.5 * (\underline{W}_{11}T_8 - \underline{W}_{11}T_9) \geq \bar{Z};$$

$$0.5 * 0.5 * 0.5 * (\bar{W}_{11}T_8 - \bar{W}_{11}T_9) \geq \underline{Z};$$

$$1.5 * 1.5 * 1.5 * (\underline{W}_{11}T_9 - \underline{W}_{11}T_3) \geq \bar{Z};$$

$$0.5 * 0.5 * 0.5 * (\bar{W}_{11}T_9 - \bar{W}_{11}T_3) \geq \underline{Z};$$

$$1.5 * 1.5 * 2.5 * (\underline{W}_{11}T_3 - \underline{W}_{11}T_7) \geq \bar{Z};$$

$$0.5 * 0.5 * 1.5 * (\bar{W}_{11}T_3 - \bar{W}_{11}T_7) \geq \underline{Z};$$

$$1.5 * 1.5 * 2.5 * (\underline{W}_{11}T_7 - \underline{W}_{11}T_6) \geq \bar{Z};$$

$$0.5 * 0.5 * 1.5 * (\bar{W}_{11}T_7 - \bar{W}_{11}T_6) \geq \underline{Z};$$

$$1.5 * 1.5 * 3.5 * (\underline{W}_{11}T_6) \geq \bar{Z};$$

$$0.5 * 0.5 * 2.5 * (\bar{W}_{11}T_6) \geq \underline{Z};$$

!Expert 1 !Criteria 2

$$1.5 * 2.5 * 1.5 * (\underline{W}_{12}T_2 - \underline{W}_{12}T_4) \geq \bar{Z};$$

$$0.5 * 1.5 * 0.5 * (\bar{W}_{12}T_2 - \bar{W}_{12}T_4) \geq \underline{Z};$$

$$\begin{aligned}
& 1.5 * 2.5 * 1.5 * (\underline{W}_{12}T_4 - \underline{W}_{12}T_7) \geq \underline{Z}; \\
& 0.5 * 1.5 * 0.5 * (\overline{W}_{12}T_4 - \overline{W}_{12}T_7) \geq \underline{Z}; \\
& 1.5 * 2.5 * 1.5 * (\underline{W}_{12}T_7 - \underline{W}_{12}T_9) \geq \underline{Z}; \\
& 0.5 * 1.5 * 0.5 * (\overline{W}_{12}T_7 - \overline{W}_{12}T_9) \geq \underline{Z}; \\
& 1.5 * 2.5 * 1.5 * (\underline{W}_{12}T_9 - \underline{W}_{12}T_3) \geq \underline{Z}; \\
& 0.5 * 1.5 * 0.5 * (\overline{W}_{12}T_9 - \overline{W}_{12}T_3) \geq \underline{Z}; \\
& 1.5 * 1.5 * 1.5 * (\underline{W}_{12}T_3 - \underline{W}_{12}T_5) \geq \underline{Z}; \\
& 0.5 * 0.5 * 0.5 * (\overline{W}_{12}T_3 - \overline{W}_{12}T_5) \geq \underline{Z}; \\
& 1.5 * 2.5 * 2.5 * (\underline{W}_{12}T_5 - \underline{W}_{12}T_6) \geq \underline{Z}; \\
& 0.5 * 1.5 * 1.5 * (\overline{W}_{12}T_5 - \overline{W}_{12}T_6) \geq \underline{Z}; \\
& 1.5 * 2.5 * 2.5 * (\underline{W}_{12}T_6 - \underline{W}_{12}T_8) \geq \underline{Z}; \\
& 0.5 * 1.5 * 1.5 * (\overline{W}_{12}T_6 - \overline{W}_{12}T_8) \geq \underline{Z}; \\
& 1.5 * 2.5 * 2.5 * (\underline{W}_{12}T_8 - \underline{W}_{12}T_8) \geq \underline{Z}; \\
& 0.5 * 1.5 * 1.5 * (\overline{W}_{12}T_8 - \overline{W}_{12}T_8) \geq \underline{Z}; \\
& 1.5 * 2.5 * 3.5 * (\underline{W}_{12}T_8) \geq \underline{Z}; \\
& 0.5 * 1.5 * 2.5 * (\overline{W}_{12}T_8) \geq \underline{Z};
\end{aligned}$$

Expert 1 | Criteria 3

$$\begin{aligned}
& 1.5 * 1.5 * 1.5 * (\underline{W}_{13}T_2 - \underline{W}_{13}T_3) \geq \underline{Z}; \\
& 0.5 * 0.5 * 0.5 * (\overline{W}_{13}T_2 - \overline{W}_{13}T_3) \geq \underline{Z}; \\
& 1.5 * 1.5 * 1.5 * (\underline{W}_{13}T_3 - \underline{W}_{13}T_4) \geq \underline{Z}; \\
& 0.5 * 0.5 * 0.5 * (\overline{W}_{13}T_3 - \overline{W}_{13}T_4) \geq \underline{Z}; \\
& 1.5 * 1.5 * 1.5 * (\underline{W}_{13}T_4 - \underline{W}_{13}T_6) \geq \underline{Z}; \\
& 0.5 * 0.5 * 0.5 * (\overline{W}_{13}T_4 - \overline{W}_{13}T_6) \geq \underline{Z}; \\
& 1.5 * 1.5 * 1.5 * (\underline{W}_{13}T_6 - \underline{W}_{13}T_7) \geq \underline{Z}; \\
& 0.5 * 0.5 * 0.5 * (\overline{W}_{13}T_6 - \overline{W}_{13}T_7) \geq \underline{Z}; \\
& 1.5 * 1.5 * 1.5 * (\underline{W}_{13}T_7 - \underline{W}_{13}T_9) \geq \underline{Z}; \\
& 0.5 * 0.5 * 0.5 * (\overline{W}_{13}T_7 - \overline{W}_{13}T_9) \geq \underline{Z}; \\
& 1.5 * 1.5 * 1.5 * (\underline{W}_{13}T_9 - \underline{W}_{13}T_5) \geq \underline{Z}; \\
& 0.5 * 0.5 * 0.5 * (\overline{W}_{13}T_9 - \overline{W}_{13}T_5) \geq \underline{Z};
\end{aligned}$$

$$1.5 * 1.5 * 2.5 * (\underline{W}_{13}T_5 - \underline{W}_{13}T_8) \geq \underline{Z};$$

$$0.5 * 0.5 * 1.5 * (\overline{W}_{13}T_5 - \overline{W}_{13}T_8) \geq \underline{Z};$$

$$1.5 * 1.5 * 2.5 * (\underline{W}_{13}T_8 - \underline{W}_{13}T_1) \geq \underline{Z};$$

$$0.5 * 0.5 * 1.5 * (\overline{W}_{13}T_8 - \overline{W}_{13}T_1) \geq \underline{Z};$$

$$1.5 * 1.5 * 3.5 * (\underline{W}_{13}T_1) \geq \underline{Z};$$

$$0.5 * 0.5 * 2.5 * (\overline{W}_{13}T_1) \geq \underline{Z};$$

$$\begin{aligned} &\overline{W}_{11}T_1 + \overline{W}_{11}T_2 + \overline{W}_{11}T_3 + \overline{W}_{11}T_4 + \overline{W}_{11}T_5 + \overline{W}_{11}T_6 + \overline{W}_{11}T_7 + \overline{W}_{11}T_8 + \overline{W}_{11}T_9 + \overline{W}_{12}T_1 \\ &+ \overline{W}_{12}T_2 + \overline{W}_{12}T_3 + \overline{W}_{12}T_4 + \overline{W}_{12}T_5 + \overline{W}_{12}T_6 + \overline{W}_{12}T_7 + \overline{W}_{12}T_8 + \overline{W}_{12}T_9 \\ &+ \overline{W}_{13}T_1 + \overline{W}_{13}T_2 + \overline{W}_{13}T_3 + \overline{W}_{13}T_4 + \overline{W}_{13}T_5 + \overline{W}_{13}T_6 + \overline{W}_{13}T_7 + \overline{W}_{13}T_8 \\ &+ \overline{W}_{13}T_9 = 1.2; \end{aligned}$$

$$\begin{aligned} &\underline{W}_{11}T_1 + \underline{W}_{11}T_2 + \underline{W}_{11}T_3 + \underline{W}_{11}T_4 + \underline{W}_{11}T_5 + \underline{W}_{11}T_6 + \underline{W}_{11}T_7 + \underline{W}_{11}T_8 + \underline{W}_{11}T_9 + \underline{W}_{12}T_1 \\ &+ \underline{W}_{12}T_2 + \underline{W}_{12}T_3 + \underline{W}_{12}T_4 + \underline{W}_{12}T_5 + \underline{W}_{12}T_6 + \underline{W}_{12}T_7 + \underline{W}_{12}T_8 + \underline{W}_{12}T_9 \\ &+ \underline{W}_{13}T_1 + \underline{W}_{13}T_2 + \underline{W}_{13}T_3 + \underline{W}_{13}T_4 + \underline{W}_{13}T_5 + \underline{W}_{13}T_6 + \underline{W}_{13}T_7 + \underline{W}_{13}T_8 \\ &+ \underline{W}_{13}T_9 = 0.8; \end{aligned}$$

$$\underline{Z} \geq \underline{Z};$$

$$\begin{aligned} &\overline{W}_{11}T_1 \geq \underline{W}_{11}T_1; \overline{W}_{11}T_2 \geq \underline{W}_{11}T_2; \overline{W}_{11}T_3 \geq \underline{W}_{11}T_3; \overline{W}_{11}T_4 \geq \underline{W}_{11}T_4; \overline{W}_{11}T_5 \geq \underline{W}_{11}T_5; \overline{W}_{11}T_6 \\ &\geq \underline{W}_{11}T_6; \overline{W}_{11}T_7 \geq \underline{W}_{11}T_7; \overline{W}_{11}T_8 \geq \underline{W}_{11}T_8; \overline{W}_{11}T_9 \geq \underline{W}_{11}T_9; \overline{W}_{12}T_1 \\ &\geq \underline{W}_{12}T_1; \overline{W}_{12}T_2 \geq \underline{W}_{12}T_2; \overline{W}_{12}T_3 \geq \underline{W}_{12}T_3; \overline{W}_{12}T_4 \geq \underline{W}_{12}T_4; \overline{W}_{12}T_5 \\ &\geq \underline{W}_{12}T_5; \overline{W}_{12}T_6 \geq \underline{W}_{12}T_6; \overline{W}_{12}T_7 \geq \underline{W}_{12}T_7; \overline{W}_{12}T_8 \geq \underline{W}_{12}T_8; \overline{W}_{12}T_9 \\ &\geq \underline{W}_{12}T_9; \overline{W}_{13}T_1 \geq \underline{W}_{13}T_1; \overline{W}_{13}T_2 \geq \underline{W}_{13}T_2; \overline{W}_{13}T_3 \geq \underline{W}_{13}T_3; \overline{W}_{13}T_4 \\ &\geq \underline{W}_{13}T_4; \overline{W}_{13}T_5 \geq \underline{W}_{13}T_5; \overline{W}_{13}T_6 \geq \underline{W}_{13}T_6; \overline{W}_{13}T_7 \geq \underline{W}_{13}T_7; \overline{W}_{13}T_8 \\ &\geq \underline{W}_{13}T_8; \overline{W}_{13}T_9 \geq \underline{W}_{13}T_9; \end{aligned}$$

$$\underline{W}_{11}T_1, \underline{W}_{11}T_2, \underline{W}_{11}T_3, \underline{W}_{11}T_4, \underline{W}_{11}T_5, \underline{W}_{11}T_6, \underline{W}_{11}T_7, \underline{W}_{11}T_8,$$

$$\underline{W}_{11}T_9, \underline{W}_{12}T_1, \underline{W}_{12}T_2, \underline{W}_{12}T_3, \underline{W}_{12}T_4, \underline{W}_{12}T_5, \underline{W}_{12}T_6, \underline{W}_{12}T_7,$$

$$\underline{W}_{12}T_8, \underline{W}_{12}T_9, \underline{W}_{13}T_1, \underline{W}_{13}T_2, \underline{W}_{13}T_3, \underline{W}_{13}T_4, \underline{W}_{13}T_5, \underline{W}_{13}T_6,$$

$$\underline{W}_{13}T_7, \underline{W}_{13}T_8, \underline{W}_{13}T_9 \geq 0.$$

4. Data and results

The study involves three sustainability criteria, ten experts, and nine different alternatives that can be seen from Tables 4 to 7. It is important to note that the study considered all the experts to be of equally important. However, it is worth noting that the OPA-G can calculate the experts' weights as well, if needed. After solving the model, weights and ranking for criteria and alternatives are shown in Tables 8 and 9. To obtain the weights of criteria and alternatives, Eqs. (5) and (6) are employed. Afterward, to extract the ranking for criteria and alternatives matrix P_{ij} has been estimated using Eq. (8).

Table 4. Experts’ opinions regarding importance of different criteria

Experts	Rank Type	Economic criterion (C1)	Social criterion (C3)	Environmental criterion (C2)
E1	Crispy Rank (CR)	1	2	1
	Grey Rank (GR)	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]
E2	Crispy Rank (CR)	1	2	1
	Grey Rank (GR)	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]
E3	Crispy Rank (CR)	1	3	2
	Grey Rank (GR)	[0.5,1.5]	[2.5,3.5]	[1.5,2.5]
E4	Crispy Rank (CR)	1	2	1
	Grey Rank (GR)	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]
E5	Crispy Rank (CR)	1	3	2
	Grey Rank (GR)	[0.5,1.5]	[2.5,3.5]	[1.5,2.5]
E6	Crispy Rank (CR)	1	1	1
	Grey Rank (GR)	[0.5,1.5]	[0.5,1.5]	[0.5,1.5]
E7	Crispy Rank (CR)	2	2	1
	Grey Rank (GR)	[1.5,2.5]	[1.5,2.5]	[0.5,1.5]
E8	Crispy Rank (CR)	1	2	1
	Grey Rank (GR)	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]
E9	Crispy Rank (CR)	2	3	1
	Grey Rank (GR)	[1.5,2.5]	[2.5,3.5]	[0.5,1.5]
E10	Crispy Rank (CR)	2	3	1
	Grey Rank (GR)	[1.5,2.5]	[2.5,3.5]	[0.5,1.5]

Table 5. Opinion of experts for the technologies against Economic criteria

Experts	Rank Type	T1	T2	T3	T4	T5	T6	T7	T8	T9
E1	CR	1	1	2	1	1	3	2	1	1
	GR	[0.5,1.5]	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]	[0.5,1.5]	[2.5,3.5]	[1.5,2.5]	[0.5,1.5]	[0.5,1.5]
E2	CR	1	2	4	2	4	5	1	3	2
	GR	[0.5,1.5]	[1.5,2.5]	[3.5,4.5]	[1.5,2.5]	[3.5,4.5]	[4.5,5.5]	[0.5,1.5]	[2.5,3.5]	[1.5,2.5]
E3	CR	1	5	2	5	2	3	4	1	4
	GR	[0.5,1.5]	[4.5,5.5]	[1.5,2.5]	[4.5,5.5]	[1.5,2.5]	[2.5,3.5]	[3.5,4.5]	[0.5,1.5]	[3.5,4.5]
E4	CR	1	5	2	3	5	4	6	3	4
	GR	[0.5,1.5]	[4.5,5.5]	[1.5,2.5]	[2.5,3.5]	[4.5,5.5]	[3.5,4.5]	[5.5,6.5]	[2.5,3.5]	[3.5,4.5]
E5	CR	1	5	1 or 2	3	6	4	3	2 or 3	5
	GR	[0.5,1.5]	[4.5,5.5]	[0.5,2.5]	[2.5,3.5]	[5.5,6.5]	[3.5,4.5]	[2.5,3.5]	[1.5,3.5]	[4.5,5.5]
E6	CR	1	2	1	1	2	1	2	1	1
	GR	[0.5,1.5]	[2.5,3.5]	[0.5,1.5]	[0.5,1.5]	[2.5,3.5]	[0.5,1.5]	[2.5,3.5]	[0.5,1.5]	[0.5,1.5]
E7	CR	1	6	3	5	7	4	8	2	9
	GR	[0.5,1.5]	[5.5,6.5]	[2.5,3.5]	[4.5,5.5]	[6.5,7.5]	[3.5,4.5]	[7.5,8.5]	[2.5,3.5]	[8.5,9.5]
E8	CR	1	4	2	3	4	3	5	2	5
	GR	[0.5,1.5]	[3.5,4.5]	[2.5,3.5]	[2.5,3.5]	[3.5,4.5]	[2.5,3.5]	[4.5,5.5]	[2.5,3.5]	[4.5,5.5]
E9	CR	1	5	2	3	5	4	5	6	7
	GR	[0.5,1.5]	[4.5,5.5]	[2.5,3.5]	[2.5,3.5]	[4.5,5.5]	[3.5,4.5]	[4.5,5.5]	[5.5,6.5]	[6.5,7.5]
E10	CR	2	4	3	1	4	3	5	1	4
	GR	[2.5,3.5]	[3.5,4.5]	[2.5,3.5]	[0.5,1.5]	[3.5,4.5]	[2.5,3.5]	[4.5,5.5]	[0.5,1.5]	[3.5,4.5]

Agricultural activity is the lifeline for human civilization. However, it is also a source of some adverse effects environment which are usually overlooked. Identifying and selecting appropriate low-carbon and sustainable technologies for the agriculture sector can reduce these adverse effects. Thus the current study identified the best low-carbon and sustainable agricultural technologies and then applied OPA-G methods to evaluate those technologies. After analyzing all experts' opinions, results show that all these technologies have some potential to be used in the agriculture sector to handle global climate change agricultural sustainability issues with varying degrees of priority. The current study finds that among all the available alternatives, integrated crop-livestock systems (ICLS), T1, constitute the best technology that can enhance food production and contribute to sustainable development while improving environmental quality by reducing net GHG emissions. The literature from different regions supports this finding. For example, Vinholis *et al.* (2021) showed that Brazil has already taken the initiative to adapt ICLS to its agriculture sector as a voluntary target of reducing emissions. By 2020 Brazil has adopted about 4 million hectares of land under ICLS and avoided 22.11 million tons of carbon dioxide (MAPA, 2019). In North America, Russelle *et al.* (2007) suggested that farmers should adapt ICLS technology to enhance firms' profitability and environmental sustainability. However, from Table 4, one can easily see the ranking of all available technologies. Figure 4 shows complete ranking.

In terms of sustainability criteria, results suggest all these technology has some viable potentiality to be used in the agricultural sector and the literature also suggests the same. But the current study did not find any literature that has suggested ranking for low carbon and sustainable agricultural technology under uncertainty. Therefore, the current study employed the OPA-G model to handle the uncertainty related to the agricultural sector and find the ranking among different alternatives. With the aid of the OPA-G method, decision-makers can genuinely enjoy a high level of flexibility in dealing with various sustainable criteria and uncertainty. Moreover, the OPA-G method does not require data normalization, a pairwise comparison matrix, and aggregating experts' opinions.

Table 6. Opinion of experts for the technologies against Social criteria

Experts	Rank Type	T1	T2	T3	T4	T5	T6	T7	T8	T9
E1	CR	3	1	2	1	2	2	1	2	1
	GR	[2.5,3.5]	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]	[1.5,2.5]	[1.5,2.5]	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]
E2	CR	1	4	5	3	4	3	2	2	3
	GR	[0.5,1.5]	[3.5,4.5]	[4.5,5.5]	[2.5,3.5]	[3.5,4.5]	[2.5,3.5]	[1.5,2.5]	[1.5,2.5]	[2.5,3.5]
E3	CR	2	3	4	2	3	1	4	4	5
	GR	[1.5,2.5]	[2.5,3.5]	[3.5,4.5]	[1.5,2.5]	[2.5,3.5]	[0.5,1.5]	[3.5,4.5]	[3.5,4.5]	[4.5,5.5]
E4	CR	2	3	1	2	4	1	2 or 3	2	5
	GR	[1.5,2.5]	[3.5,4.5]	[0.5,1.5]	[1.5,2.5]	[3.5,4.5]	[0.5,1.5]	[1.5,3.5]	[1.5,2.5]	[4.5,5.5]
E5	CR	2	3	1	4	3	5	3	2	3
	GR	[1.5,2.5]	[3.5,4.5]	[0.5,1.5]	[3.5,4.5]	[3.5,4.5]	[4.5,5.5]	[3.5,4.5]	[1.5,2.5]	[3.5,4.5]
E6	CR	1	2	1	1	2	3	1	2	1
	GR	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]	[0.5,1.5]	[1.5,2.5]	[3.5,4.5]	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]
E7	CR	5	8	4	6	2	1	9	3	7
	GR	[4.5,5.5]	[7.5,8.5]	[3.5,4.5]	[5.5,6.5]	[1.5,2.5]	[0.5,1.5]	[8.5,9.5]	[3.5,4.5]	[6.5,7.5]
E8	CR	5	3	4	4	3	2	1	3	4
	GR	[4.5,5.5]	[3.5,4.5]	[3.5,4.5]	[3.5,4.5]	[3.5,4.5]	[1.5,2.5]	[0.5,1.5]	[3.5,4.5]	[3.5,4.5]
E9	CR	4	2	3	4	2	5	5	4	2
	GR	[3.5,4.5]	[1.5,2.5]	[3.5,4.5]	[3.5,4.5]	[1.5,2.5]	[4.5,5.5]	[4.5,5.5]	[3.5,4.5]	[1.5,2.5]
E10	CR	3	4	4	5	5	3	1	3	5
	GR	[3.5,4.5]	[3.5,4.5]	[3.5,4.5]	[4.5,5.5]	[4.5,5.5]	[3.5,4.5]	[0.5,1.5]	[3.5,4.5]	[4.5,5.5]

Table 7. Opinion of experts for the technologies against Environmental criteria

Experts	Rank Type	T1	T2	T3	T4	T5	T6	T7	T8	T9
E1	CR	3	1	1	1	2	1	1	2	1
	GR	[2.5,3.5]	[0.5,1.5]	[0.5,1.5]	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]	[0.5,1.5]	[1.5,2.5]	[0.5,1.5]
E2	CR	3	2	5	4	2	1	1	5	4 or 5
	GR	[2.5,3.5]	[1.5,2.5]	[4.5,5.5]	[3.5,4.5]	[1.5,2.5]	[0.5,1.5]	[0.5,1.5]	[4.5,5.5]	[3.5,5.5]
E3	CR	3	2	4	3	2	3	1	5	4
	GR	[2.5,3.5]	[1.5,2.5]	[3.5,4.5]	[2.5,3.5]	[1.5,2.5]	[2.5,3.5]	[0.5,1.5]	[4.5,5.5]	[3.5,4.5]
E4	CR	3	1	4	2	4	3	1	4	3
	GR	[2.5,3.5]	[0.5,1.5]	[3.5,4.5]	[1.5,2.5]	[3.5,4.5]	[2.5,3.5]	[0.5,1.5]	[3.5,4.5]	[2.5,3.5]
E5	CR	2	1	3	3	2	3	1	4	3 or 4
	GR	[1.5,2.5]	[0.5,1.5]	[2.5,3.5]	[2.5,3.5]	[1.5,2.5]	[2.5,3.5]	[0.5,1.5]	[3.5,4.5]	[2.5,4.5]
E6	CR	2	2	3	1	2	2	1	3	2
	GR	[1.5,2.5]	[1.5,2.5]	[2.5,3.5]	[0.5,1.5]	[1.5,2.5]	[1.5,2.5]	[0.5,1.5]	[2.5,3.5]	[1.5,2.5]
E7	CR	9	3	7	6	5	4	1	8	2
	GR	[8.5,9.5]	[2.5,3.5]	[6.5,7.5]	[5.5,6.5]	[4.5,5.5]	[3.5,4.5]	[0.5,1.5]	[7.5,8.5]	[1.5,2.5]
E8	CR	3	1	3	2	4	2	1	4	3
	GR	[3.5,4.5]	[0.5,1.5]	[3.5,4.5]	[1.5,2.5]	[3.5,4.5]	[1.5,2.5]	[0.5,1.5]	[3.5,4.5]	[3.5,4.5]
E9	CR	2	1	3	4	3	3	1	4	5
	GR	[1.5,2.5]	[0.5,1.5]	[3.5,4.5]	[3.5,4.5]	[3.5,4.5]	[3.5,4.5]	[0.5,1.5]	[3.5,4.5]	[4.5,5.5]
E10	CR	4	1	5	4	3	3	1	3	2
	GR	[3.5,4.5]	[0.5,1.5]	[4.5,5.5]	[3.5,4.5]	[3.5,4.5]	[3.5,4.5]	[0.5,1.5]	[3.5,4.5]	[1.5,2.5]

Table 8. Weights and ranking of criteria

Criteria	Lower limit	Upper limit	Average weights	Rank
Economy	0.2792	0.4557	0.3674	2
Social	0.1820	0.2232	0.2026	3
Environmental	0.3388	0.5211	0.4300	1

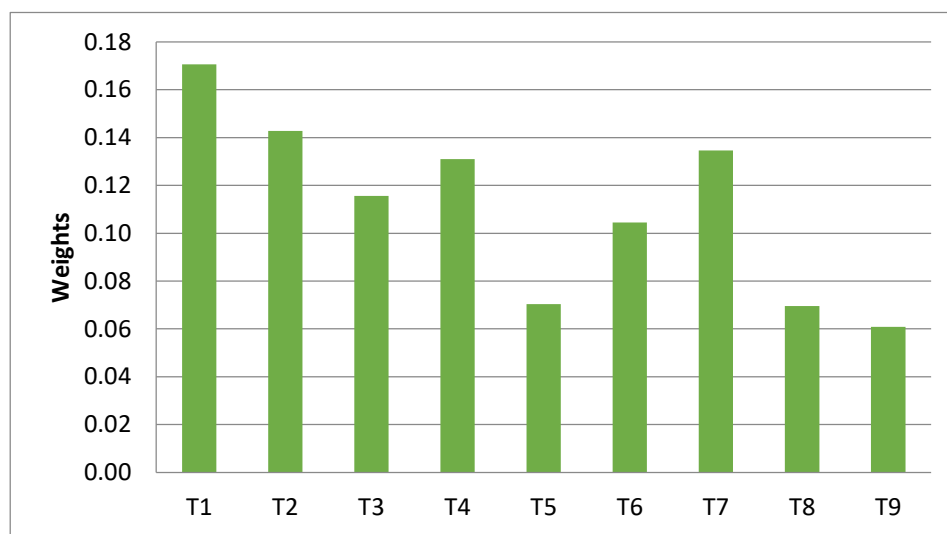
5. Conclusion and recommendations

Climate change is a global issue, and the agricultural sector is an integral part of it. Agriculture activities significantly influence the economy, society, and environment, which are the main indicator of sustainable development. Using low-carbon and sustainable agricultural technology can help mitigate the adverse effect on the environment and increase global food security. But selecting appropriate low-carbon and sustainable agricultural technology for the agricultural industry becomes a big problem. There are many MCDM methods in literature to help decision-makers, but several methods are not equipped to deal with uncertainty in information. Thus, this study employed the Grey Ordinal Priority Approach (OPA-G), a modern multi-attribute decision-making technique that will help decision-makers select the best possible alternatives/technologies for the agricultural industry.

To achieve sustainable development goals (SDGs), the contribution of the agriculture sector cannot be neglected. Implications of low-carbon and sustainable agricultural technology is an inevitable choice for government and policymakers in developed and developing countries. Despite the negative effects from the agriculture sector, it would be easier to mitigate climate change than any other sector. This study identified a number of well-known key low-carbon and sustainable agricultural technologies that have proven their usefulness for all agriculture activities in most countries and have the potential to be used. The implications of these technologies in the agriculture sector can help tackle global climate change and ensure global food security.

Table 9. Weights and ranking of technologies

Alternatives	Lower limit	Upper limit	Average weights	Rank
Integrated crop-livestock systems (T1)	0.1313	0.2100	0.1706	1
No-tillage (T2)	0.0979	0.1877	0.1428	2
Integrated crop-livestock-forest system (T3)	0.0971	0.1342	0.1156	5
Conservation agriculture (T4)	0.1007	0.1614	0.1310	4
Integrated Soil Fertility Management (T5)	0.0600	0.0808	0.0704	7
Agroforestry (T6)	0.0932	0.1157	0.1045	6
Carbon sequestration (T7)	0.1097	0.1596	0.1346	3
Crop diversification (T8)	0.0602	0.0788	0.0695	8
Soil and water conservation (T9)	0.0499	0.0720	0.0609	9

**Figure 4.** The ranking of technologies based on the OPA-G

Although the theory of the OPA-G model seems superior in many aspects when compared with the classical MCDM theories, it can further be improved. Identifying qualified experts for the data collection of different alternatives based on a sustainable approach has brought more research questions for this model. Experts' opinions are crucial for the decision-making process; experts' unfair or biased judgment can affect the final results. A standardized objective methodology to prioritize experts is needed. The development of a tool to predict the level of reliability can improve its effectiveness. The model should be applied to solve diverse problems to better understand its limitations and strengths in the future.

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