Drone as a Service (DaaS) in promoting Cleaner Agricultural Production and Circular Economy for Ethical Sustainable Supply Chain Development

Abstract

In order to grow the food the world needs, there is a pressing need to gain a more detailed understanding of how innovative solutions can be incorporated into the agricultural supply chains, particularly within production, for environmentally, economically, ethically and socially viable food production. Despite a number of innovative solutions available, many challenges in agricultural supply are still prevalent, with researchers to date largely focusing on these challenges in isolation, as opposed to exploring the relationships held between these challenges. Thus, supported by Circular Economy, Agriculture, Industry 4.0 literature and expert opinions, agricultural supply chain challenges are modelled and analysed using ISM methodology to help uncover 12 agricultural challenges which ultimately impede goods moving within the supply chain. Findings discovered that the *Unproductive Workers* and *Pesticide Hazards* are the key drivers of agricultural challenges. The ISM Hierarchical model elucidates research propositions and a parsimonious model for future research.

Keywords: Drone as a Service (DaaS), Circular Economy, ReSOLVE Framework, Industry 4.0, ISM, MICMAC

1. Introduction

The world's population continues to increase, thus having real implications for global food demand whilst necessitating the agricultural activity to expend in order to keep pace. It is expected that the food production will grow by two thirds in 2050 to secure adequate nutrition for an additional of two billion people (United Nation, 2015). With the modern agricultural system claimed to be wasteful (Toop et al., 2017) and entailing ethical concerns (Hendrickson and James, 2005), as well as the risk of reduction in crops yields due to the impact of climate change and Covid-19 (de Preneuf, 2020), there is a significant demand to establish an sustainable approach to supply chains in agriculture, particularly within production, based on Circular Economy (CE) principles and the utilisation of innovative technologies as for profitable business practices. Unlike the linear economy concept of 'use and dispose', a circular approach to resources offers the potential for a multitude of socio-economic and environmental benefits (Patwa et al., 2020). However, factors such as lack of innovative approaches and technology utilisation for cleaner production and perception on facing uncertainty in terms of costs and return on investment, has meant supply chains have struggled with completely adopting CE principles (Jabbour et al., 2018).

Supply chains by nature are complex and require oversight across each of its stages, non-more so than food supply networks, which extends from the farmers, through to consumers, and has an increased emphasis placed on the movement of its produce, given its perishable nature. According to Rushton et al. (2006), movement of goods infers to physical good movements and storage, from when it was produced up until when it is consumed. However, within agricultural supply chains, the agricultural producers through to the manufacturers make up the essential components of the supply chain (Akkerman et al., 2010), which can ultimately have an impact across the entire supply chain. A Sustainable Supply Chain (SSC) will ensure good governance practices throughout the food lifecycle, including helping the production of food in an environmentally, economically, ethical and socially viable way. As such SSC becomes more pertinent in ensuring business continuity through optimisation of operational costs and maintenance of product integrity.

Despite the technological advancements of recent times, there remains a pressing need to find innovative solutions to the challenges faced within agriculture. The increased focus on agricultural technology is unsurprising, given agriculture's role in reducing poverty and stimulating economic growth (Martin, 2018). This is compounded by the expected increase of the world's population to almost 9.1 billion, especially in developing countries. Therefore, in order to secure food for this expanded global population, study suggest the production of food should grow by 70% (Vasconez et al., 2019). Henceforth, the rise in population present a constant threat to global food security (Coale and Hoover, 2015), further emphasising the crucial role of agricultural practices in providing food for future generations and significantly contributing towards food security.

Given the rise in Industry 4.0 (I4.0) based technologies, which facilitates automation, real time data capture and predictive capabilities, the traditional challenges associated to CE adoption and ethical approach to SSC may be better managed, through the application of such technologies. Nonetheless, there has been fairly limited knowledge on the relationships between CE, I4.0 and ethics, as they are often explored separately. This calls for a sound understanding on how the interplay between CE principles, I4.0 technology and ethics can assist in the application of Cleaner Agricultural Production (CAP).

There is a growing stream of studies exploring I4.0 within agriculture, or known as Agriculture 4.0 (Belaud et al., 2019). For instance, Lezoche et al. (2020) explore both the implications and challenges of Agri-food 4.0 in their study and in doing so, touch upon some of the key operational challenges relating to the implementation of I4.0 technology. Moreover, Tantalaki et al. (2019) reveals that big data technologies creates a promising future in agriculture, through providing real-time solutions as the result of agricultural automation. It is also argued that agriculture 4.0 provides efficiency in food production, but also place emphasis on it potentially entailing social and environmental costs – hence demanding investigation on how it could be approached ethically (Rose and Chilvers, 2018). Thus, while emphasis has been on advancing agricultural practices, the focus has been largely on technology. For instance, researchers are also increasingly exploring Artificial Intelligence (AI) techniques to assist farmers in meeting high agricultural demands, such as Young (2020), who explores how AI can develop environmentally-conscious agriculture and reducing deforestation for food production. Similarly, Jha et al. (2019) highlight the role of automation practices through key technologies such as Internet of Things (IoT), Connected Devices, , AI and Deep learning in overcoming traditional agricultural challenges such as pesticides hazards, irrigation management, as well as managing the impact of agricultural practices on the environment. Therefore, more can be done in terms of understanding the role of both technologies and CE principles in driving changes within agriculture.

Given the emerging gaps between the interlaces of SSC, CE principles, ethics and AI technology in agriculture, this paper aims to identify relationships between key agricultural challenges in the backdrop of a SSC, whilst also exploring how I4.0 related technologies may assist in overcoming such key challenges. This is to ultimately offer useful insights that could drive greater efficiencies in agricultural supply networks through an ethical manner, in response of rising environmental challenges and shifts in demand, consumption patterns and consumer attitude.

The effective movement of good is becoming increasingly important in the present, uncertain, and critical times. Many studies have explored agricultural supply chain challenges, with focus has been placed largely on the transportation (Higgins et al., 2018), storage (Alawneh and Zhang, 2018), food loss (Aschemann-Witzel et al., 2017) and delivery of goods (Qin et al., 2019). Yet, little focus has been placed on establishing contextual relationships between factors which influence and impact agri-supply chain. Chapman (2010) reported that almost one-third of food loss occurs along the supply network, were attributed to stakeholders along the downstream supply, such as consumers and retailers – signposting a pressing need to further explore the factors which impact the supply of produce from upstream supply perspective, such as food producers. Accordingly, Parfitt et al. (2010) posit poor harvesting techniques, as well as plant diseases and pests contributes towards food waste within the harvesting and storage phases of food supply chains.

The extant literature indicates that a little focus to date has been placed on agricultural supply chain through I4.0 and CE lenses. Therefore, the focus of this research is placed on key agricultural challenges within upstream supply chain, through I4.0 offerings, ethics and CE theoretical lenses. By doing so, findings from this research have the potential to offer more holistic insights, which not only identifies agricultural supply chain issues, but also explores how these factors may interact and impact one another. This allows identification of the root cause issues within agricultural supply chain, permitting an exploration of its potential solutions.

Panetto et al. (2020) highlight the importance of I4.0 technologies such as smart farming, sensors, and real-time virtualisation in supporting farming and overcoming challenges within agricultural supply chains. However, despite a plethora of challenges being identified, they mainly relate to environmental and societal challenges, such as food shortages and security, and pollution and depleting natural resources (Bonneau and Copigneaux, 2017), and only limited practical approaches have been taken to address these. This highlights an urgent need and further impetus for the food industry to adopt newer approaches to ensure productivity, sustainability and competitiveness (Miranda et al., 2019).

While the extant literature is not short of technological approaches – e.g. RFID, Augmented reality, 3D printing, Simulation, Autonomous vehicles, Robots, Cloud computing, AI and Big data to support the application of technologies within the supply networks, further insights are required to recognise and fully comprehend the nature of these challenges. This is particularly important given that the supply chain is made up of various interrelated components that contributes to its complexity. Moreover, while the solutions have a very operational focus, little studies to date have explored how they can also assist in advocating and endorsing CE principles. Accordingly, the paper focuses on the subsequent research questions:

> RQ1. What are the current key challenges that impact cleaner agricultural production within the supply chain?
>
> RQ2. To what extent are these key challenges interrelated? If so, what kind of relationships exists?
>
> RQ3. What is the potential of I4.0 and CE in overcoming the identified challenges and in contributing towards creating cleaner, ethical agricultural production?

The aim is to extend beyond identifying the relationships between the factors identified in Fig.4. by exploring the role I4.0 can play in minimising or overcoming agricultural challenges, through the lens of CE principles.

This article is structured as follows. Section 2 outlines the contextual relationship of agricultural and food challenges in agricultural, CE, I4.0 concepts as well as Ethics and CAP. Section 3 presents the research methodology, which is followed by the result and analysis in Section 4 Section 5 offers discussions on the results and Section 6 draws some conclusions, highlights the research limitations, before concluding with the future research agenda resulting from this present work.

2. Literature review

2.1 **Circular Economy*: ReSOLVE Framework***

The conceptualisation of CE has been widely debated since the last decade (Murray et al., 2017), resulting into various definition of the CE. In general, a CE model can be referred to as a non-linear, regenerative and restorative by design practices aiming to detach consumption of non-renewable resources from growth, opposing the conventional 'take-make-waste' economy model (MacArthur et al., 2016). Despite there not being an unified definition, the CE's 3Rs principles have been applied extensively across, macro and micro levels, including cleaner production contexts (Sousa-Zomer et al., 2018). For instance, the concept of 'reduce' was adopted by Su et al. (2013) and Winans et al. (2017) in their research, 'reuse' concept in Castellani et al. (2015), and recycle in Birat's (2015) research.

Findings of an extensive review of the CE literature suggest that a gap between the concepts and the actual application of these principles is evident, despite of the recent academic focus and emphasis on CE. For instance, studies have highlighted a disconnect between CE concepts and their use (Sauvé et al., 2016), leading to renewed calls for an investigation into how CE's principles, objectives and aims can be translated better into meaningful actions (Pauliuk, 2018). In overcoming this, Suárez-Eiroa et al. (2019) identify operationally focused CE principles, centred mainly on resource conservation, managing inputs and outputs system, system optimisation and creating awareness around CE. Moreover, Hobson (2016) places emphasis on technology advancements amongst other key factors as playing a vital role in translating CE principles into meaningful actions, for example through achieving optimal use of material and minimising waste production.

Likewise, Bekchanov and Mirzabaev (2018) also highlight how these principles can be implemented and aided through CE enabling technologies, to overcome adverse environmental issues and to enhance cost efficiency (Geissdoerfer et al., 2017). While the 3R's, have varying hierarchical importance, ultimately aiming to reduce resources being used can be seen as the leading principle within a CE system (Su et al., 2013). As such, the Reduce CE principle is the underpinning focus of this research from an agricultural context. Despite the focus on 'reduce', the research looks beyond just 'reducing' resources, by exploring I4.0 as a driver to offer a more holistic impact by reconfiguring the system to eliminate hazardous material, through resource longevity and system regeneration (MacArthur and Waughray 2016). In other words, the research looks to identify how 'reducing' resources use through I4.0 may help minimise adverse impact on the environment, increase efficiency and help maintain natural systems.

With this in mind, it is imperative to apply CE principles, beyond merely conceptualising it's potential, whilst also exploring how technological advancements, such as I4.0 technologies can help play a role in achieving CE principles. In facilitating this, Jabbour et al. (2018), put forward guidelines to improve the utilisation of CE principles for organizations engaged in I4.0 activities. Their roadmap is underpinned by the ReSOLVE framework, which can serve as an effective approach in assisting organisations to implement CE principles. Accordingly, the ReSOLVE framework is a central element in this ressarch, to help gain an insights into how I4.0 and CE can support clean, ethical agricultural production. This framework (i.e. **Re**generate, **S**hare, **O**ptimise, **L**oop, **V**irtualise and **E**xchange) established by the Ellen MacArthur Foundation to facilitate CE-friendly decision making across various contexts, sets out to reconfigure the system for the purposes of eliminating waste, enabling material reuse and to preserve the natural environment. Reconfiguration of the system seeks to eliminate activities that adversely impacts the environment as well as human health, including the generation and release of hazardous materials. In farming practices, this principle concerns with, among others, the use of pesticide and fertiliser for crops maintenance, as well as forest conversion activity for new farm opening which causes pollution. For instance, the conversion of forest to agricultural land in Cerrado, Brazil i.e. the second largest biome in South America – has severely endangered various flora and fauna species, putting them into extinction (Strassburg et al., 2016). Meanwhile, the burning of trees due to Amazon deforestation for cattle-ranching and soy-farming has released greenhouse effects (Bax et al., 2016; Walker et al., 2000) and caused serious public health issue of malaria as the burnt forest turns into the breeding ground for mosquito (Hahn et al., 2014).

Moreover, the regenerative agriculture practices recycling farm waste and using composted materials to return valuable nutrients to support soil health, which is of paramount in determining healthy growth of crops that would bring about positive yields (Devkota et al., 2019). In this respect, the small scale farmers are prone to adopt practices such as integrated water resources management (Rahaman and Varis, 2005) and self-maintained habitat (Jackson, 2005). Supporting the same principle, a larger scale farm are more inclined into no-till or reduced-ill farming method (Chauhan et al., 2013). Over time, this method would dramatically increase yield due to the deepening of the topsoil (Devkota et al., 2019; Jouzi et al., 2017), which then requires lesser fertiliser application (Bashir et al., 2019; Dong et al., 2019).

2.2 Ethical and cleaner production

Ethics prevails as an important topic in the field of agriculture. Nonetheless, the broadly agreed upon "code of ethics" remains absent. This study approaches ethics in the context of "farm structure", "food security", and "environmental impacts".

Focusing on the general economic and social features of the farm such as its size and working condition of the farm workers, the debates on "farm structure" interrogate the implication of certain methods in farming on both – the workers well-being and the environment, which leads to the debates on applying substitute methods. Meanwhile, the "food security" discourses focusing on balancing the worldwide food supply chain with the agronomy advancement agriculture (i.e. providing sufficient food for the growing world population) raise concerns over crops protection against diseases due to modern environmental threats and bioterrorism, inviting enhanced safety solutions. Lastly, ethics related arguments on "environmental impact" question the legitimacy of crop production management, with common arguments on the safety of food and workers, overuse of water and soil, as well as repercussion on the ecosystem infringing the natural habitat of the wildlife. This has challenged both the researchers and farmers to revaluate ethical position and the existing approaches to farming, especially the standpoint on the conservation of materials and reducing environmental impact – i.e. the concept of cleaner production.

Research suggests that connecting innovation to these concerns is pivotal in enabling ethical solutions (Lubberink et al., 2017). Hence, conceptualising how the use of I4.0 technology could mitigate the concerns of ethics in agriculture is important, as well as following the conduct of CP by envisaging their inter-relationships using the widely utilised Circular Economy's ReSOLVE framework (see Fig.1).

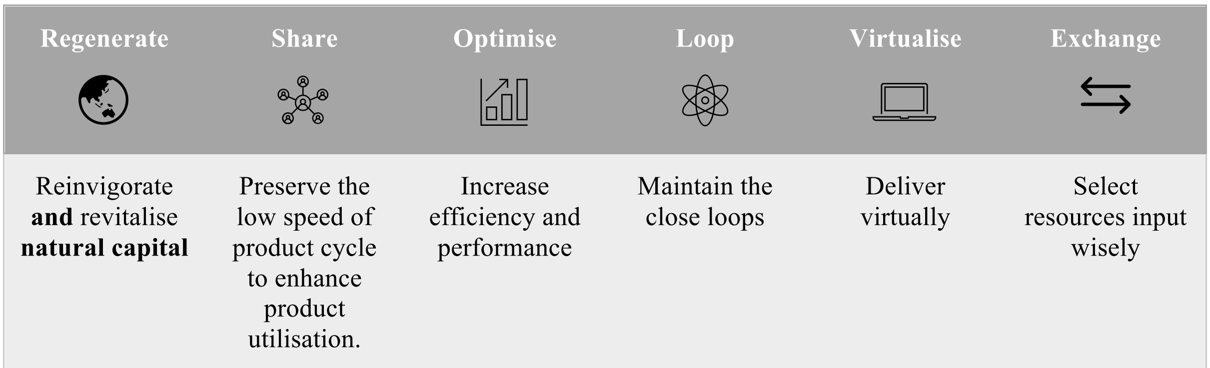

Fig.1: ReSOLVE Framework (adapted from Ellen MacArthur Foundation, SUN and McKinsey Center for Business and Environment, Growth Within: A Circular Economy Vision for a Competitive Europe (2015). Based on S. Heck, M. Rogers, P. Carroll, Resource Revolution (2015)

2.3 Industry 4.0 and Circular Economy for Cleaner Production

Sustainable supply chain management suggests the continuous accountability for risk and negative impact led by actions throughout the supply chain. Studies suggest SSC is hampered by myriad of challenges particularly supplier-led (Yadav et al., 2020). As the initial input contributor, suppliers can primarily trigger and facilitate the smooth SSC adoption (Jin et al., 2017). Therefore, close monitoring of suppliers' activities is vital to avoid disturbance in SSC system (Gopal and Thakkar, 2016).

Multitude of studies (Fatorachian and Kazemi, 2018; Jabbour et al., 2018) suggest I4.0 and CE weave the future of many industries. There are steady increase in adoption of these concepts in achieving global sustainability due to rapid evolution of technology, especially the one supporting automation and data intelligence, as well as reverse logistics practices (Hofmann and Rüsch, 2017). In SSC, I4.0 is heavily utilised to encourage digitisation, whilst forming a systemic approach, which enables the use of sustainable resources to avoid "harming the environment" (Mastos et al. 2020; Moeuf et al., 2018). This includes tracking of anomalies within the supply chain for early interventions. Because of this, Bibby and Dehe (2018) agree that the co-evolution of I4.0 and CE enables, drives and determines the successful adoption of SSC practices in diverse industries, including agriculture. An increasing number of manufacturing industries are undergoing a transformation from linear to CE, accordingly, I4.0 is considered as key innovative technology in facilitating this.. However, much of the academic focus to date within CE has been on products as opposed to the service sector. This paper is concerned with Drones-as-a-Service, a new emerging and trending area of research and application.

Exploring the extant I4.0 literature, it is evident the focus has largely been on 'cyber-physical systems', IoT, and cloud manufacturing and analytics (Kang et al. 2016; Zhong et al., 2017), rather than drones. While there remain limited insights into I4.0 technologies and CE, a handful of studies have attempted to explore the synergies and connections between I4.0 and organisational sustainability, however, the focus again, has been on cyber-physical systems, smart factory and additive printing (Stock and Seliger 2016), virtualization of manufacturing execution systems, cyber physical system, service oriented manufacturing systems (SoMS) (Trentesaux et al., 2016) and smart production systems, IoT, automation (Waibel et al. 2017), at the expense of drones.

The application of drones (remotely unmanned controlled aircraft) originated from the military, however, is now being utilised across various industries, for many purposes, such as emergency services, traffic management, logistics and distribution (Environmental Technology, 2018). However, research pertaining to drones has highlighted the operational challenges of implementing this technology. Zhang and Kovacs (2012) suggest that drones are a cheaper and more convenient alternative than satellites and planes, as the former offer simpler working mechanisms, have a better sensor and camera optionality and most importantly in context of agriculture, offer frequent repetition of the flight over agriculture fields of produce. Yet, Khanal et al. (2017) in their review of precision agriculture highlight that despite all the opportunities and potential of unmanned aerial systems such as drones, high operating costs and a shortage of companies offering cost-effective solutions impedes the use of drones in precision agriculture. There are divergent views on whether the agricultural sector has fully reaped the benefits from these disruptive technologies advancements, as other sectors. Nonetheless, scholars and practitioners believe in the potential of I4.0, such as Robotics and AI in transforming the agricultural sector to Agriculture 4.0 is beyond recognition (Wolfert et al., 2017). Sharing the same tenet, this paper seeks to understand the challenges faced by the agriculture sector in regard to cleaner, ethical productions and threats to establishing a SSC, which can be overcome by the use of AI technology, or in specific – the AI Drone.

Despite technology being a central point of discussion when exploring ethical, sustainable practices, one cannot overlook the role of stakeholders in this regard, thus wider questions relating to the moral disposition and values of agricultural stakeholders and what these values translate to in practice should also be taken into consideration (Meijboom and Brom, 2012). While Table 1 (see below) presents a holistic view of agricultural challenges, and more specifically within Agri-tech, a focal point of interest for this paper is to identify which of the challenges are the key drivers and have most impact on cleaner agricultural production.

	Area of focus	Source(s)
AgriTech Studies	Implementation issues	Lindblom et al., 2017
	Ethical implications	Frankelius et al., 2019; Gallenti et al., 2019; Millar, 2000; Van der Burg et al., 2019
	Data-driven management	Eastwood et al. 2012
	Movement towards enacting and adapting smart farming technologies	Eastwood et al., 2017; Gnauer et al., 2019
	Dilution of cultural fabric of farming	Burton et al., 2012
	Legal awareness – New traffic space	Reger et al., 2018
Agriculture challenges	Food security	Lindblom et al., 2017
	Reduced quality of cultivated products	Shiva, 2016
	Pesticides related health hazards	Emran et al., 2020; Shammi et al., 2018; Sharifzadeh et al., 2019; Sruthi et al., 2017
	Increased environmental pollution	Ampaire et al., 2020; Audate et al., 2019; Collins et al., 2019; Karanja et al., 2019; Okumah et al., 2018
	Ecological imbalance	Peng et al., 2019
	Uncontrolled irrigation and soil erosion	Hillel et al., 2008
	Decreased migration	Vasconez et al., 2019

Table 1

Agri-tech focus and challenges

3. ISM Methodology

Interpretive structural modelling (ISM) is a methodical and cooperative method of analysing interrelationships between variables (Warfield, 1974). It allows us to establish a structural model between variables that are derived from experts' opinions (Luthra et al., 2014). Moreover, MICMAC analysis explores and analyses the challenges for CAP based on their driving and dependency powers. Although there are various other techniques including analytic hierarchy process, analytic network process, DEMATEL, graph theory, structural equation modelling, etc., an evaluation of ISM with the other techniques conclude that ISM-MICMAC based technique is relatively robust and more fit in analysing contextual relationships between variables when there is not any prior understanding of their interlinkages from the existing literature (Mangla et al., 2018).

In this study, the integrated ISM-MICMAC approach is implemented using various steps as follows: First, the variables linked with the research problem at hand are identified In the context of this research, twelve key challenges of CAP are studied from the current literature and are listed as the variables, namely V1, V2, V3,…,V12 (see

Table **2**).

Table 2
Major CAP challenges

#V	Challenge	Brief description	Sources
V1	Illegal deforestation	Monitoring and controlling illegal deforestation for new farm opening and excessive cutting of trees. It is particularly difficult to monitor the reforestation activities.	Appiah et al., 2009; Bax et al., 2016; Rajao et al., 2020; Walker et al., 2000

V2	Lack of efficiency	Efficiency, by reducing costs and increasing the yield. Yields efficiency remains a key challenge within agriculture.	Devkota et al., 2020; Huang et al., 2017; Scupola and Zanfei, 2016
V3	Lack of accurate predictions for seasonal output	Agriculture is largely dependent on weather conditions; despite technological advancements - predicting accurate output for a season is also difficult due to unexpected weather conditions. By having accurate weather forecasts can help inform growers when is the best time to apply pesticides - reduce wastage and prevent drainage to river that could cause water pollution threatening health and safety of society or animals consuming the water.	Liu and Huang, 2013; Bagheri et al., 2019
V4	Theft and sabotage	Security is a key agricultural challenge, as plantations/ farms located in rural areas that are often exposed to thefts.	Clack, 2013; OECD, 2012
V5	Inaccurate seeding	Direct seeding method is a deterrent to the growers that apply no-till farming. To avoid tilling and to benefit from benefit from higher yields, healthier crops and less damage to the environment, the seeding process should be mechanised.	Elliot, 2016; Diwate et al., 2018
V6	Unproductive workers	Unproductive workers is a key issue in agriculture settings. If worker are not performing their duties, due to either lack of knowledge, skills or negligence can significantly impact yield.	Diwate et al., 2018
V7	Pesticides application and hazards	Reducing the health and safety risk for workers who are exposed pesticide. The measurement of 'just right quantity' of pesticide use of pesticides is difficult.	Emran et al., 2020; Shammi et al., 2018; Sharifzadeh et al., 2019; Sruthi et al., 2017
V8	Workers health and safety risks	Maintaining the health and safety of agriculture workers is very important and can be a challenge, particularly when the workers access risky and remote areas (e.g. mountains, hills, forest, etc.)	Román-Muñiz et al., 2006; Lunner-Kolstrup and Ssali, 2016
V9	Movement of produce within supply chain	The movement of agricultural produce along the supply chain whilst maintaining food safety and security	Naik and Suresh, 2018; Akkerman et al., 2010; Smith, 2008; Wognum et al., 2010; Parafitt et al., 2010
V10	Pollution	Haze and preventing bushfires are extremely difficult especially across large areas of agricultural land. There is a need to find ways to fight bushfire and open burning (common for replanting).	Nazeer et al., 2016; Okumah et al., 2018; Asumadu-Sarkodie and Owusu, 2017; Pan et al., 2016
V11	Soil Compaction	Soil compaction resulting from growers and farmers walking on fertile land whilst working in the fields, which adversely impacts root growth. There is a need maintain optimum level of soil compaction for vegetable farms	Talbot et al. 2018; Huang et al., 2017
V12	Disease of plants	Plant diseases is a key challenge, therefore ways in which preventing the crops disease has a significant impact on yield.	Bagheri et al., 2019; Boyd et al., 2013; Sundström et al., 2014; Gilligan, 2008; Stuthman et al., 2007

Second, develop contextual interactions between listed challenges of CAP through questionnaire and data collection. Third, the structural self-interaction matrix (SSIM) is developed using the pairwise relations between identified CAP's challenges through the majority opinions by the experts. Fourth, the initial reachability matrix (IRM) is developed using the SSIM. IRM is then translated into final reachability matrix (FRM) by testing transitivity in IRM. Fifth, the driving and dependence power of each challenge is calculated by counting the total number of binary '1s' both transitive as well as non-transitive row-wise and column-wise in the given FRM. Sixth, different partitions levels are developed by identifying the same elements in both reachability set and antecedent set. When every element of reachability set is found is antecedent set, a third set is created, called intersection set and it essentially contains the same element(s) as in the reachability set. Reachability set constitutes of challenges it impacts whereas antecedent set consists of the challenges itself and other challenges that affect this challenge. Intersection set consists of the set of collective factors from both reachability as well as antecedent sets and different levels are identified in every iteration when reachability set becomes equal to the intersection set. Seventh, MICMAC graph is constructed using the driving powers and dependencies of every challenge. Finally, structural model using ISM is formed through the challenges of CAP through the digraph. The used methodology is shown in Fig 2. using ISM-MICMAC flowchart.

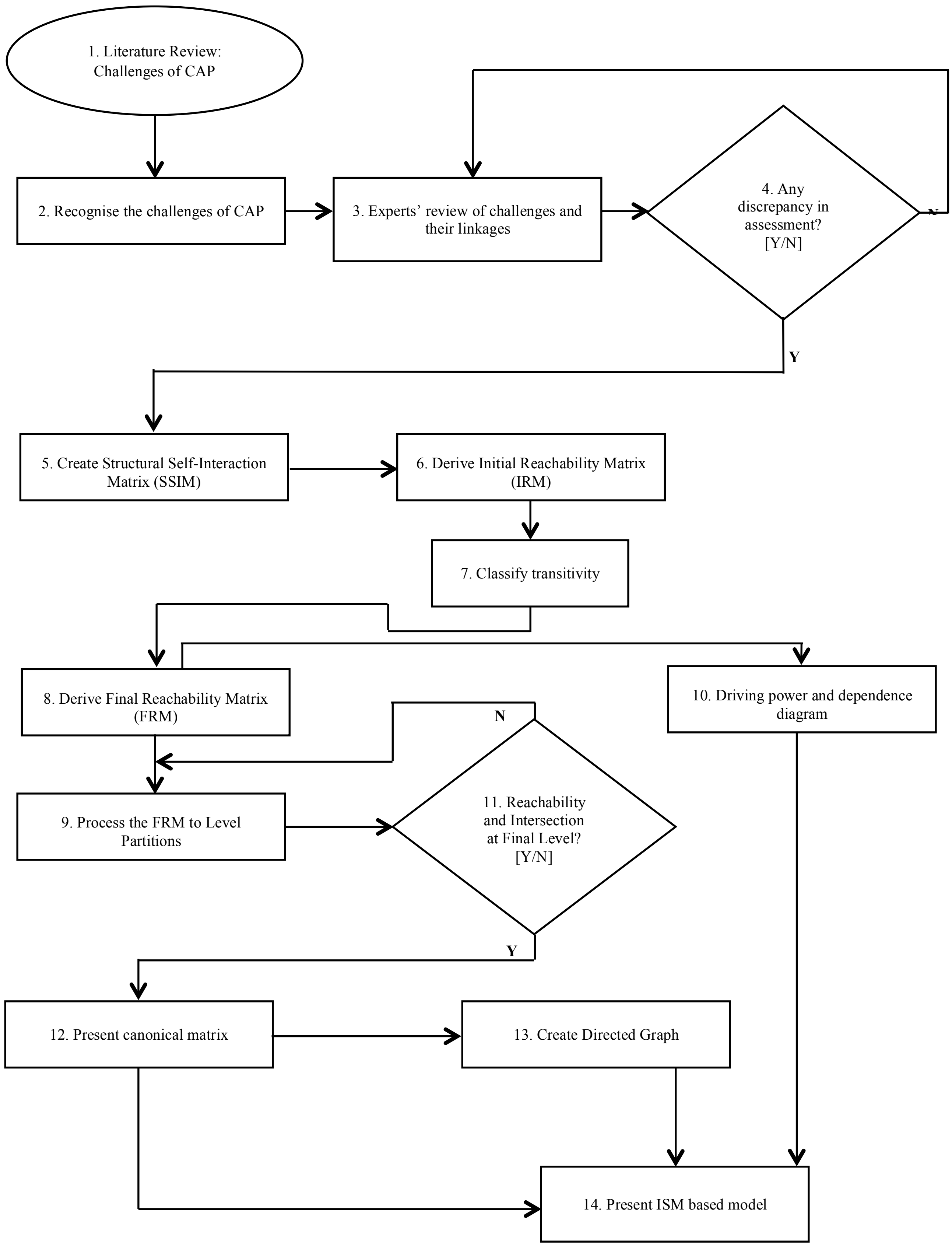

Fig. 2. ISM-MICMAC flow chart (Adapted from Rana et al., 2019b)

4. Data Analysis

Data associated to the interlinks between the challenges of CAP were collected from nine experts, each whom had practical working experience in various companies, particularly in agriculture and technology domains and also the researchers who are the experts of technology adoption, CE and supply chain management. These individuals were reached through the approach of convenient sampling as one of the co-authors is work colleague of one cohort of respondents and another co-author knows the industrial experts from personal contact. These experts work with various companies and held different positions including Regional Director, Vice President, Software Engineer, and Data Scientist presents respondents' demographic traits as shown below.

Table 3.
Expert profiles

Experts (with pseudo name)	Job Role	Gender	Age group	Work experience
T.O.	Researcher in Logistics	Male	30-39	10 years
E.B.	Researcher in Food Security	Female	20-29	7 years
K.M.	Researcher in Data Analytics	Male	30-39	11 years
A.O.	Researcher in Technology Adoption	Female	40-49	15 years
D.N.	Researcher in geospatial and remote sensing, precision agriculture specialist	Female	30-39	10 years
C.K.	Artificial intelligent and blockchain Specialist	Male	60-69	30 years
R.K.	Artificial intelligent specialist.	Male	40-49	15 years
J.O.	Software engineer, drone as service specialist	Male	20-29	6 years
R.L.	Precision agriculture, drone as service specialist	Male	30-39	10 years

4.1 Self-structured interaction matrix (SSIM)

The SSIM was developed (see

Table 1) that has been filled in with related links between each pair of challenges of CAP by collating different matrices retorted by individual experts. SSIM is developed by using four different ciphers i.e. V, A, X, and O, which have the following interpretation:

V: Variable i helps achieve or has influence on Variable j;

A: Variable j helps achieve or has influence on Variable i;

X: Variables i and j help achieve or influence each other; and

O: Variables i and j are not related to each other (Hughes et al., 2016; Rana et al., 2019a)

Table 1
Self-structured interaction matrix

i/j	12	11	10	9	8	7	6	5	4	3	2
1	O	X	V	O	V	O	A	O	X	O	V
2	V	A	A	V	A	A	A	A	A	A	
3	A	A	A	V	O	A	A	A	A		
4	O	O	V	V	A	O	A	O			
5	O	A	O	V	A	O	A				
6	V	V	X	V	X	A					
7	A	O	V	O	V						
8	A	O	A	V							
9	A	O	A								
10	A	V									
11	V										

4.2 Initial reachability matrix (IRM) and final reachability matrix (FRM) development

In the further procedural step for the proposed framework using ISM, SSIM based matrix is converted into a matrix of two-fold numbers (i.e. 0 and 1). This is done by replacing 'V', 'A', 'X' and 'O' in Table 4 (i.e. SSIM) into the values of '0s' and '1s' as per the following procedures (Rana et al., 2019b):

- For each 'V' in SSIM, include '1' in (i, j) and '0' in (j, i) cell,
- For each 'A' in SSIM, include '0' in (i, j) and '1' in (j, i) cell,
- For each 'X' in SSIM, include '1' in (i, j) and '1' in (j, i) cell, and
- For each 'O' in SSIM, include '0' in (i, j) and '0' in (j, i) cell.

By converting all the symbols using the above procedures in SSIM, the IRM of the challenges of CAP is presented in **Error! Reference source not found.** below.

Table 5
Initial reachability matrix (IRM)

V#	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
V1	1	1	0	1	0	0	0	1	0	1	1	0
V2	0	1	0	0	0	0	0	0	1	0	0	1
V3	0	1	1	0	0	0	0	0	1	0	0	0
V4	1	1	1	1	0	0	0	0	1	1	0	0
V5	0	1	1	0	1	0	0	0	1	0	0	0
V6	1	1	1	1	1	1	0	1	1	1	1	1
V7	0	1	1	0	0	1	1	1	0	1	0	0
V8	0	1	0	1	1	1	0	1	1	0	0	0
V9	0	0	0	0	0	0	0	0	1	0	0	0
V10	0	1	1	0	0	1	0	1	1	1	1	0
V11	1	1	1	0	1	0	0	0	0	0	1	1
V12	0	0	1	0	0	0	1	1	1	1	0	1

[Note: V1: Illegal deforestation; V2: Lack of efficiency; V3: Lack of accurate predictions for seasonal output; V4: Theft and sabotage; V5: Inaccurate seeding; V6: Unproductive workers; V7: Pesticides application and hazards; V8: Workers health and safety risks; V9: Movement of produce within supply chain; V10: Pollution; V11: Soil compaction; V12: Disease of plants]

Furthermore, FRM is derived from IRM by implementing transitivity rule as presented in Table 5. Transitivity in the FRM is represented using '1*'. We present transitivity using the following example: If X is linked to Y (X→Y) and Y is linked to Z (Y→Z) then the relationship between X and Z could be shown using (X→Z). This approach is used to identify transitivity to present the FRM through the notations of '0', '1', and '1*' as follows:

Step 1. Initiate using Row 1 and go down until the last row (i.e. Row n). Classify every occurrence of '1' in Row 1(j) and use them to assist the further step. Ignore every reference for n:n such as 1:1, 2:2, etc. Step 2. For every occurrence of a '0' across the entire row (j), keep finding the specific column 'i' and make a reference for each previously mentioned '1' from the initial row but now alongside column. Step 3. If we find a match in Step 2, then it is converted into any occurrences of '0' for the earlier setup to '1*' and move on to the further occurrence of '0' across the row (j). Keep working on with these steps until the entire complicated matrix is verified for transitivity (Hughes et al., 2016).

Table 6
Final reachability matrix (FRM)

V#	1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1*	1	1*	1*	0	1	1*	1	1	1*
2	0	1	1*	0	0	0	1*	1*	1	1*	0	1
3	0	1	1	0	0	0	0	0	1	0	0	1*
4	1	1	1	1	0	1*	0	1*	1	1	1*	1*
5	0	1	1	0	1	0	0	0	1	0	0	1*
6	1	1	1	1	1	1	1*	1	1	1	1	1
7	1*	1	1	1*	1*	1	1	1	1*	1	1*	1*
8	1*	1	1*	1	1	1	0	1	1	1*	1*	1*
9	0	0	0	0	0	0	0	0	1	0	0	0
10	1*	1	1	1*	1*	1	0	1	1	1	1	1*
11	1	1	1	1*	1	0	1*	1*	1*	1*	1	1
12	0	1*	1	1*	1*	1*	1	1	1	1	1*	1

[Note: V1: Illegal deforestation; V2: Lack of efficiency; V3: Lack of accurate predictions for seasonal output; V4: Theft and sabotage; V5: Inaccurate seeding; V6: Unproductive workers; V7: Pesticides application and hazards; V8: Workers health and safety risks; V9: Movement of produce within supply chain; V10: Pollution; V11: Soil compaction; V12: Disease of plants]

4.3 Partitioning of levels

CAP challenges are divided into various levels of hierarchical structure using the matrices of IRM and FRM. Diverse sets including reachability, antecedent and intersection sets are formed to divide these factors into various stages. For example, reachability set is a set of factors constituting the factor on its own and other factors influenced by it whereas antecedent set consists of a factor itself and other factors, which influence this factor. However, intersection set is the set of common variables between reachability and antecedent sets (Dwivedi et al., 2017). Challenges would be marked as Level I when both reachability as well as intersection sets become equal (see Table 1). For example, challenge such as 'movement of produce within supply chain (C9)' has been assigned to Level I because for this challenge the element (i.e. V9) for both reachability as well as intersection sets is same. After assigning Level I to 'V9', this is removed from the rest of the procedure. This process is iterated until each challenge has been assigned a label. Partitioning of levels performed a total of five iterations to develop the ISM model where the challenges 'V6' (unproductive workers) and 'V7' (pesticides application and hazards) are labelled to Level V (see Table 8).

Table 7
Level partition – Iteration

V#	**Reachability Set: R(Pi)**	**Antecedent Set: A(Pi)**	**Intersection Set: R(Pi)∩A(Pi)**	**Level**
1	1,2,3,4,5,6,8,9,10,11,12	1,4,6,7,8,10,11	1,4,6,8,10,11	
2	2,3,7,8,9,10,12	1,2,3,4,5,6,7,8,10,11,12	2,3,7,8,10,12	
3	2,3,9,12	1,2,3,4,5,6,7,8,10,11,12	2,3,12	
4	1,2,3,4,6,8,9,10,11,12	1,4,6,7,8,10,11,12	1,4,6,8,10,11,12	
5	2,3,5,9,12	1,5,6,7,8,10,11,12	5,12	
6	1,2,3,4,5,6,7,8,9,10,11,12	1,4,6,7,8,10,12	1,4,6,7,8,10,12	
7	1,2,3,4,5,6,7,8,9,10,11,12	2,6,7,11,12	2,6,7,11,12	
8	1,2,3,4,5,6,8,9,10,11,12	1,2,4,6,7,8,10,11,12	1,2,4,6,8,10,11,12	
9	9	1,2,3,4,5,6,7,8,9,10,11,12	9	I
10	1,2,3,4,5,6,8,9,10,11,12	1,2,4,6,7,8,10,11,12	1,2,4,6,8,10,11,12	
11	1,2,3,4,5,7,8,9,10,11,12	1,4,6,7,8,10,11,12	1,4,7,8,10,11,12	
12	2,3,4,5,6,7,8,9,10,11,12	1,2,3,4,5,6,7,8,10,11,12	2,3,4,5,6,7,8,10,11,12	

In this way, Table 8 provides a challenge or the list of challenges at every iteration by eliminating the relevant challenge(s) from the previous step and classifying the new challenge(s) by the matched reachability set with the antecedent set and identifying the variable(s) for which both sets (i.e. reachability and antecedent sets) were equal.

Table 8
Levels of challenges of CAP

Iteration	Level#	Challenges of CAP
1^{st}	I	Movement of produce within supply chain (V9)
2^{nd}	II	Lack of efficiency (V2)
		Lack of accurate predictions for seasonal output (V3)
		Disease of plants (V12)
3^{rd}	III	Theft and sabotage (V4)
		Inaccurate seeding (V5)
4^{th}	IV	Illegal deforestation (V1)
		Workers health and safety risks (V8)
		Pollution (V10)
		Soil compaction (V11)
5^{th}	V	Unproductive workers (V6)
		Pesticides application and hazards (V7)

4.4 Development of the canonical form of the FRM matrix

A canonical matrix is developed in the next step in the ISM process. This matrix (see Table 9) is established by clustering challenges in the same level across the rows and columns of the FRM. The variables are arranged in the table in the sequence of the levels assign to them as per Table 7. This matrix could be considered as another more convenient form of FRM for drawing the ISM model. Furthermore, the driving power and dependence power of each challenge is computed by counting the number of '1s' row-wise and column-wise respectively in Table 8, which help us position these challenges in the MICMAC diagram in the next section.

Table 9
Canonical form of the FRM matrix

V#	9	2	3	12	4	5	1	8	10	11	6	7	Level	DRP
9	1	0	0	0	0	0	0	0	0	0	0	0	I	1
2	1	1	1	1	0	0	0	1	1	0	0	1	II	7
3	1	1	1	1	0	0	0	0	0	0	0	0	II	4
12	1	1	1	1	1	1	0	1	1	1	1	1	II	11
4	1	1	1	1	1	0	1	1	1	1	1	0	III	10
5	1	1	1	1	0	1	0	0	0	0	0	0	III	5
1	1	1	1	1	1	1	1	1	1	1	1	0	IV	11
8	1	1	1	1	1	1	1	1	1	1	1	0	IV	11
10	1	1	1	1	1	1	1	1	1	1	1	0	IV	11
11	1	1	1	1	1	1	1	1	1	1	0	1	IV	11
6	1	1	1	1	1	1	1	1	1	1	1	1	V	12
7	1	1	1	1	1	1	1	1	1	1	1	1	V	12
DPP	12	11	11	11	8	8	7	9	9	8	7	5	-	106

[Legend: DPP: Dependence Power; DRP: Driving Power]

4.5 MICMAC analysis

MICMAC analysis is aimed to understand the driving power and dependencies of every challenge within the ISM. Populating the driving and dependence power within the MICMAC determines the positions of variables across one of the four quadrants in the MICMAC matrix (see Fig. 3). Therefore, the quadrant where the given factor is situated in the matrix indicates it overall driving or dependence nature and also the position of variables across various levels of the hierarchy in the ISM model. These four quadrants are (Rana et al., 2019a, 2019b):

1. **Independent** – defines those variables which are of weak dependence and high driving power and are very frequently seen as key factors driving other factors up the hierarchy in the ISM model. These variables are generally seen toward the bottom of the ISM model.
2. **Dependent** – defines variables that have high dependence and low driving power. These variables are the ones that are largely driven by other variables down the hierarchy in the ISM model and generally found at the top level of the model.
3. **Autonomous** – defines variables which have both low driving as well as dependence power. They have very least influence or impact and manage only limited connections with the other variables in the model.
4. **Linkage** – variables are the one with the high driving and high dependence power. They are found to be unstable as an outcome and any action taken on such variables is likely cause a parallel reaction influencing the given and other variables.

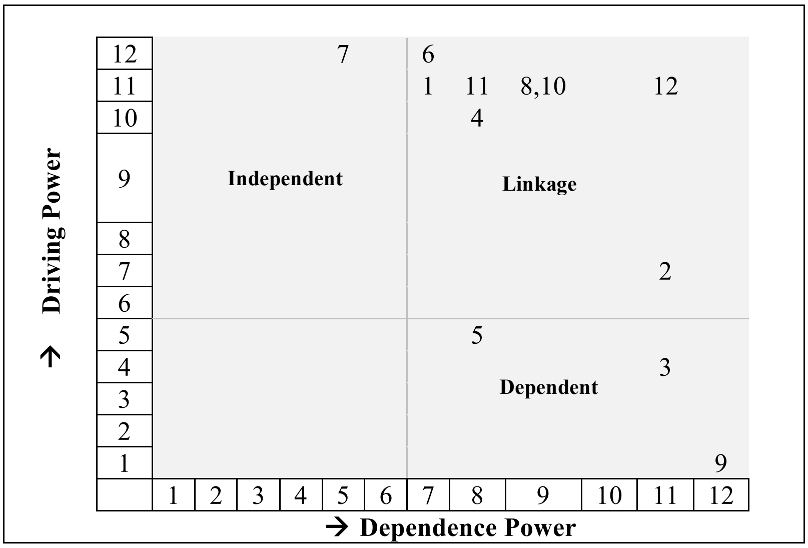

Fig. 3. MICMAC

Most of the variables in the MICMAC matrix are within linkage quadrant with only a handful of them lie in Dependent and Independent quadrants. This clearly indicates that majority of the variables are with moderate to high driving power and dependencies. This cluster designates that a vast number of variables that lie between the bottom and top level in the ISM model, which indicate they have both driving and dependence power. The key characteristic of the variables under Linkage is that because of their nature and greater number of linkages, any failure between them may have a knock-on consequence and prospective to trigger failure among other variables (Rana et al., 2019a).

The highest dependence power of ‘V9’ under Dependent quadrant indicates this variables as the most highly dependent variable with ‘V5’ and ‘V3’ being the variables with high dependence but moderate driving power as well. On the other hand, due to highest driving and lowest Dependence power ‘V7’ is considered as the only variable in Independent quadrant. Variable ‘V6’ also possesses the highest driving power and the modest dependence power and supplemented by the ISM model by having positioned at the bottom of the model.

4.6 ISM model

The last stage of the ISM process is to build the model. This model highlights the variables by showing the relationships between variables. All different variables are positioned across various levels in the hierarchy based on their driving and dependence power and the links between them are presented by taking reference from the FRM. The levels of variables are also linked with the MICMAC diagram as shown in Fig. 2. The top level (i.e. V9) of the ISM model is deriving from Level I partitioning and is also supported by MICMAC with the highest dependence power. The next three variables (i.e. V2, V3 and V12) just down to Level I is filtered out from Level II partitioning and they also tend to match with their position with the next higher dependence power of these variables. The further next level of iteration (i.e. Level III) populates two variables (i.e. V4 and V5), which demonstrate certain level of both driving as well as dependence power. The next to the bottom level of variables (i.e. V1, V8, V10 and V11) is the outcome of Level IV partitioning and these variables are more of driving power oriented variables with moderate dependence power. This could be easily recognised through their positions at the Linkage quadrant, which show the high driving power for all of them with varying but moderate dependence power. Finally, last two variables (i.e. V6 and

V7) are filtered out at the Level V iteration and they could be seen to demonstrate the highest driving power from the MICMAC diagram. The interrelationships between variables at the same level and across the next upper level are established using the FRM matrix and this could be seen from the ISM model presented in Fig. 4.

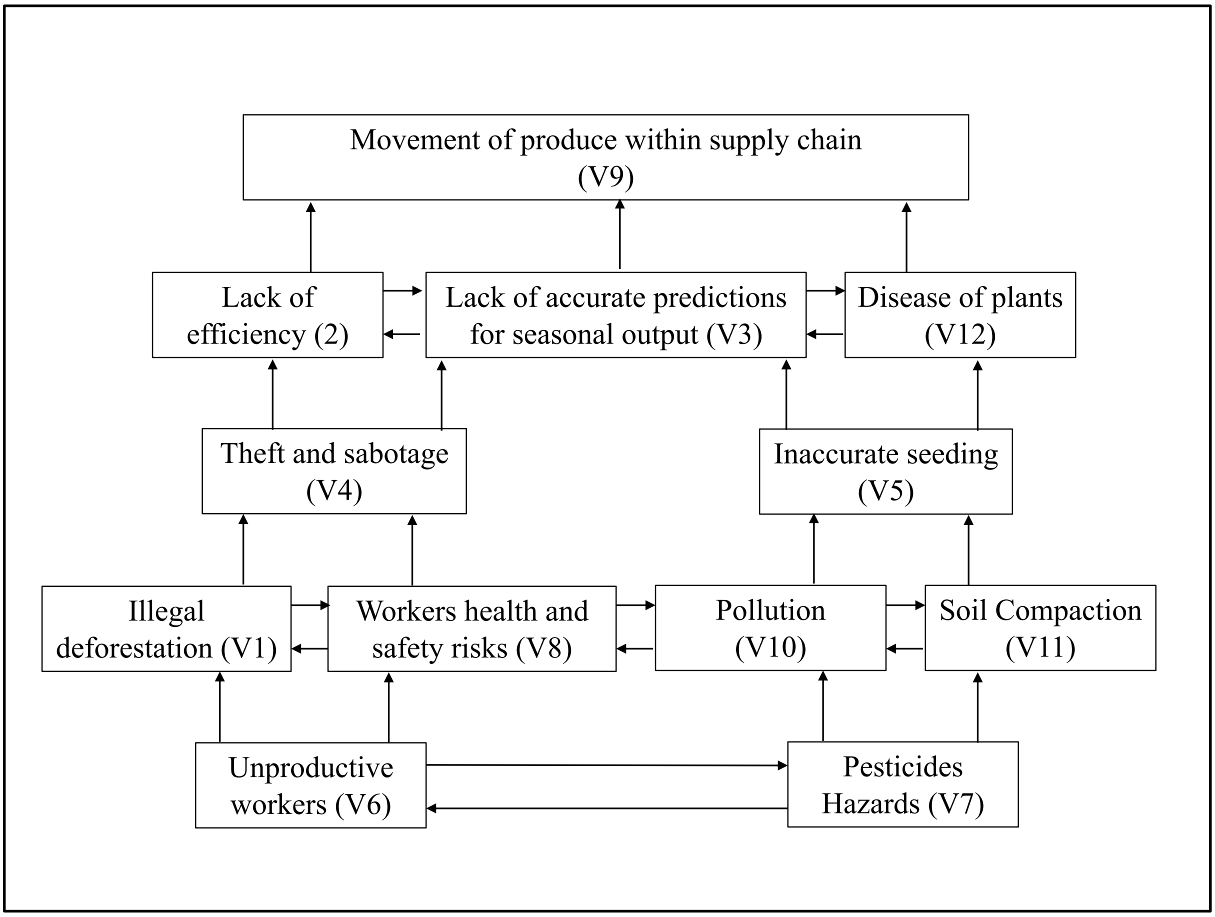

Fig. 4. ISM model for challenges of CAP

5. Discussion

The ISM model (see Fig. 2) shows the unproductive workers (V6) and pesticides hazards (V7) co-create at least ten key challenges in the context of CAP. More specifically, this highlights that in order to overcome issues relating to the movement of produce within agri-supply chains, agricultural producers must explore ways in which to minimise the hazards resulting through pesticide exposure. In addition to these challenges, workers health and safety risks (V8) and pollution (V10) also interdependently influence one another and act as major challenges for CAP.

Based on the ReSOLVE framework, the application of drones offers many opportunities in overcoming agricultural challenges, offering sustainable solutions and promote more ethical agricultural practices by addressing the “farm structure”, “food security” and “environmental impact” concerns, as well as increase adoption of CAP, as depicted in Fig. 5.

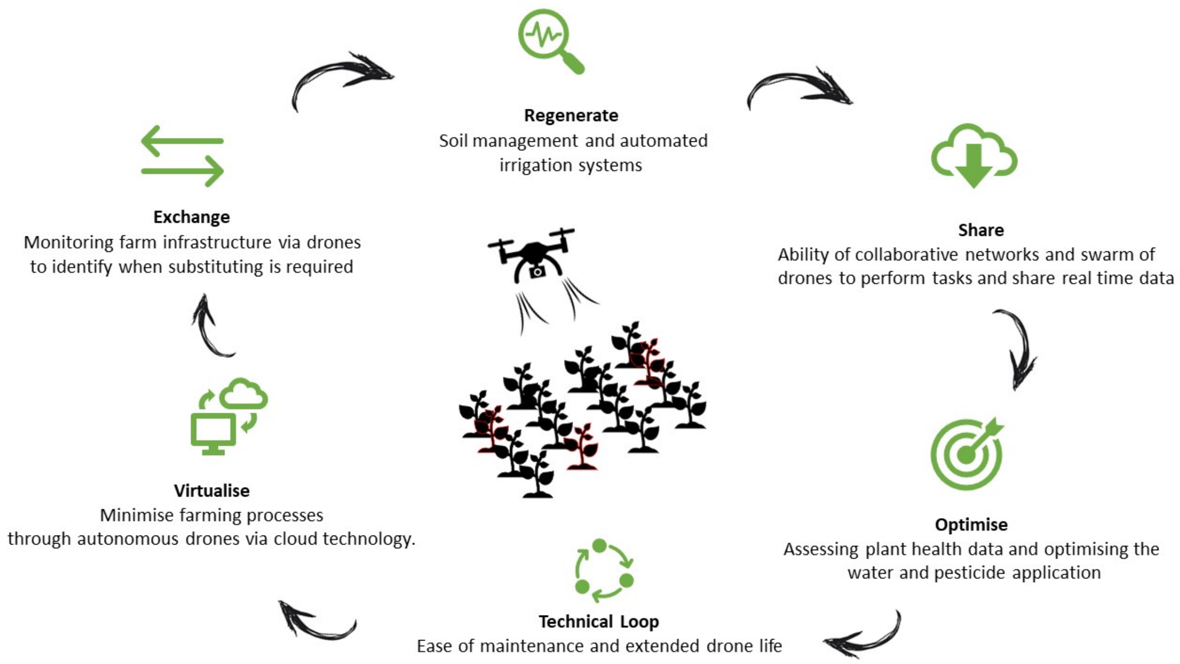

Fig. 5: Drones ReSOLVE framework application

Based on the tenet of shifting to renewable resources facilitated by the biological cycles, "**regenerate**" insists the conservation and rehabilitation of farming system by strengthening the vitality of farm soil, and topsoil regeneration. This is attainable through the use of I4.0 technology available on drones such as sensor to automate irrigation systems based on real-time weather (MacArthur and Waughray, 2016), as well as to assess it (Mazur, 2016). This is made possible through a high-technology hyper spectral sensor, also known as 'thermal sensors' (Spalević et al. 2018: 98). This is particularly important to curb the growth of weeds in an overly moist soil condition, which can curtail yields to more than half (Abouziena and Haggag, 2016). Accordingly, weed management can also be maintained through data collected from drones, as such monitoring weed communities, particularly the allergen-category breed that also threatens human health, which indirectly assist in preventive healthcare measures.

The Internet of Things (IoT) enables effective communications not just between people, but also between machines. This enables accurate predictions of when and where the machineries or equipment are needed for use in farming, hence allows them to be shared between the farmers, rather than owned (i.e. "**share**" concept). Machine-to-machine communication also allows the mobilisation of a swarm of drones to perform tasks in large size farms, reducing the manpower needs. Furthermore, the use of sensors could help performance monitoring, which prevent breakdown that could be disruptive to the supply chain – i.e. food security.

Through data captured from drones, one is able to assess plant health as images allow farmers to investigate leaf defoliation resulting from lack of water, which may damage plants are adversely impact production yields (Erickson et al., 2004). On top of this, the real-time data informs the decision of pesticide application based on crops' health. These capabilities help to decrease wastes by optimising the water and pesticide application, which is another important concept of CE framework (i.e. "**optimise**"), allowing more the farmers to have more controls in managing their own performance (Hofmann and Rüsch 2017).

Unlike other machines used in agricultural, drones have very little moving parts to wear out. In most cases, drones could last up until the flight firmware went outdated. In this case, drones are more capable in maintaining the close loop of the technological cycle (i.e. "**loop**" concept). Because of this minimum 'down-time', farmers are able to keep the business running over a protracted time period as opposed to the non-drone utilisation.

The advancement of AI technology has allowed the drones to function autonomously and even 'make their own decisions'. The autonomous drones could help the farmers to perform routine tasks, without direct human input, such as surveying a fence line and capturing images, before comparing the images and prompting the farmers of the discrepancies between historical and updated data (images). These functionalities are a direct application of the '**virtualise'** concept, where the physical activities are replaced with virtual or services. On top of reducing the risk of human safety and error, which is part of the concerns with regards to ethics in agriculture, the virtualise of (drone) services potentially increases yield due to lower turn-around time for decision and intervention.

Supporting the application of new technologies to substitute the old ones, the "exchange" concept promotes responsible consumption of the renewable resources while limiting the use of finite resources – which is in line with the use of drones in agriculture. Where the wind turbine or solar panels are used in farms, the utilisation of drones for preventive in monitoring the 'fitness' of solar panels or wind turbine is essential to avoid downtime due to power disruptions. This is another fit between drones and CE principles, as well as ethics in the context of agriculture.

The application of drones offers many opportunities in overcoming agricultural challenges and offering sustainable solutions for CAP. For instance, drones' capability to assess the irrigation or drainage of agricultural terrain through a specialised sensor (Mazur, 2016, Spalević et al. 2018) helps to stun the overuse of water and control the weeds growth, which indirectly cut the use of pesticide. Through data captured from drones, one is able to assess plant health as images allow farmers to investigate leaf defoliation resulting from lack of water, which may damage plants, are adversely impact production yields (Erickson et al., 2004). Bekchanov and Mirzabaev (2018), in their research apply CE principles to minimise pollution and enhance soil fertility through reduction of fertilizers and pesticides use in the agriculture practice. Similarly, based on the findings from the analysis, this research explores how efficient use of resources may help in reducing the application of pesticides within agricultural settings.

Arguably, the I4.0 technologies could be the catalyst for CE principles and ethical, transparent agriculture to flourish, by providing real data informing decision to apply pesticide on targeted crops, that does not only assist in designing out waste and pollution, but also could facilitate the production of a healthier consumer food – which is more ethical practice.

The I4.0 drone application of pesticides can have positive society-wide benefits, beyond just the economical, cost savings associated with the efficient use of pesticides, thus allowing farmers and other food producers to significantly reduce the use of pesticides, whilst also driving CE principles. Pesticides can adversely impact the environment, human health and also livestock. According to Choudhary et al. (2018), pesticides are also being detected in freshwater supplies, animal foods, which are exposed to such hazardous substances from a number of sources, such as pollution and pesticides use against insects. Thus, through the reduce principle, the precision application of pesticides via I4.0 can assist in efficient use of resources, design out waste and pollution, through effective and precise application and can contribute towards generative natural systems, by not contaminating water supplies and livestock feeds. This therefore highlights the potential of I4.0 in applying CE principles, for

CAP, which have wide reaching impact and effective. The consequences of not adopting this approach are depicted in Fig. 6.

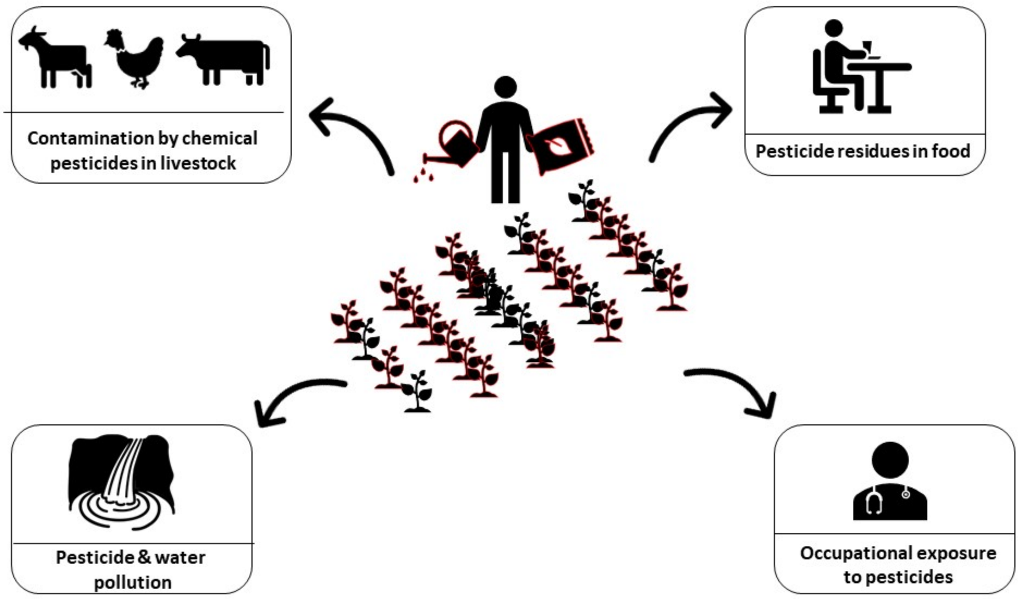

Fig. 6. Ethical challenges resulting from pesticides use

Supporting this further, drones can also assist in categorising crops on the areas under monitoring, which can add significant value to farming activities where the ability to observe seedling on the soil surface is key – such as the corn field. Another key advantage of drones is the ability in which data can be obtained at a faster rate, thus allowing for actions to be taken more proactively. The data can also be captured relating to soil health, water management and the application of pesticides, thus promoting regenerative agriculture, where focus is on optimising the use of resources instead of diminishing them (Rodale Institute, 2014).

While much of this is reported, there are little insights into the perceptions and understanding of these applications from the context of the agricultural stakeholders, such as the workers in the agricultural fields. The highlighted challenges triggered from unproductive workers (V6) and pesticides hazards (V7), leads to workers health and safety risks (V8), pollution (V10), soil compaction (V11) and the potential of illegal deforestation (V1), which then in turn trigger theft and sabotage (V4) and inaccurate seeding (V5), which principally translate to plant diseases (V12) and inefficient and inaccurate seasonal output (V2 and V3) all which hinder and inhibit movement of produce within the supply chain (V9). These hierarchical relationships are logical, given that it highlights the importance of productive workers in the upkeeping of the physical dimensions of agriculture, such as security, as well as the role of pesticides exposure, which impacts workers health and therefore adversely impacting the health of yield and plants, thus leading to lack of produce in the agricultural supply chain.

In order to realise the opportunities presented by all such approaches, there is a crucial demand to enable appreciation of the various collaboration types which can take place within the AI technology and the agricultural sector. Miranda et al. (2019) offer insights into this by highlighting the varying forms of humans-technologies collaborations in achieving this. They firstly propose the current state of art, referred to as human-human collaboration, in which humans participate without the means of technology in the agricultural system, which can be considered the current status. This is followed by human-machine collaboration, attributing the interplay between human and numerous technologies and devices, which within agri-food settings, is mainly for monitoring or automation purposes. Thirdly, the authors propose Machine-Machine collaboration, such as robots, UAVs, and automated systems that have cognitive abilities to sense, decide and act without human intervention.

When contextualising findings from this research in line with Miranda et al. (2019) proposed collaborations, it can be argued that the Machine to Machine interface may help overcome the issues relating to the movement of good. This is especially useful given that the driving factors underpinning and influencing the other key challenges are related to humans i.e. unproductive workers and pesticide hazards. Thus, with the human entirely out of the control loop and not being able to intervene, it may be worthwhile exploring this as future research. Though, given the Organizational, infrastructural, skills, training and adoption challenges highlighted in recent research (Lezoche, 2020) the human-machine collaboration seems more of a likely and realistic option.

5.1 Contributions to theory

There are a lack of previous studies, which have explored key challenges relating to agricultural supply chain in detail. More specifically, the research contributions of this study are articulated through combining existing agricultural, I4.0 and CE literature, to identify key challenges and possible solutions to agricultural supply chain issues. In doing so, this paper can be considered as one of the first, on CAP, which tries to organise its challenges and integrate them in a hierarchical model through ISM. Accordingly, this research has identified key agricultural issues impeding the movement of food produce along agricultural supply chain and as a result, this has assisted in generating a parsimonious model, which can be further tested through empirical research. Prior to this study, it was evident that the extant literature on CE has been rather largely viewed in context of products rather than services and not largely from agricultural settings. Taking this further, CE lenses are applied for service providers within agricultural context and aim to provide guidelines to agricultural service providers to explore CE. There are also a lack of studies, which have investigated the relationships between agricultural challenges, thus by applying ISM, the proposed research uncovers a number of interdependent relationships between agricultural challenges, which researchers can explore in future research. Moreover, through the application of the ISM approach, this research also minimises the gap between practice and theory by incorporating key insights from experts and practitioners rather than taking an entirely academic focus.

5.2 Implications for practice

The findings from this study present a number of practical implications on a local level for agricultural producers as well as offer more broader implications in terms of policy recommendations. Firstly, the extant literature is dominated by studies focusing on ways agricultural producers can increase their yield. By establishing relationships between agricultural challenges, agricultural producers and farmers have an opportunity to a take a more focused approach at tackling issues which are drivers for many of the challenges that lead to lower yield. For instance, the findings highlight how unproductive workers can lead to a host of agricultural issues, which in the first instance may seem unrelated. Therefore, by ensuring workers are productive and supported through apt knowledge and skills can help impact the overall yield.

Furthermore, the findings highlight the underlying role of pesticide hazards and its application, in impacting movement of goods within the supply chain. Though studies have previously emphasised much emphasis on pesticide hazards and its adverse effect on health issues, this research emphasises that the pesticide hazards have wider-reaching impact, beyond personal health, in which it also impacts other aspects of agricultural supply chain. Thus, it is imperative for both agricultural producers and also policymakers to find ways in which pesticide exposure is minimised.

However, with this said, there is a pressing need for not only agricultural/rural landowner and policy makers to engage with these findings, but also for the hands-on farmers and operational agricultural workers, to be aware of such challenges, given the provenance of agricultural challenges identified in this research are applicable to operational, agricultural workers. Therefore, it is suggested that policymakers exert much effort on educating and highlighting the issues related to the agricultural challenges to the actual workers, thus willingness to engage on their part is imperative.

6. Proposed theoretical model and propositions

This research aims to extend beyond identifying the relationships between the factors identified in Fig.7. by exploring the role I4.0 can play in minimising or overcoming agricultural challenges, through the lens of CE principles.

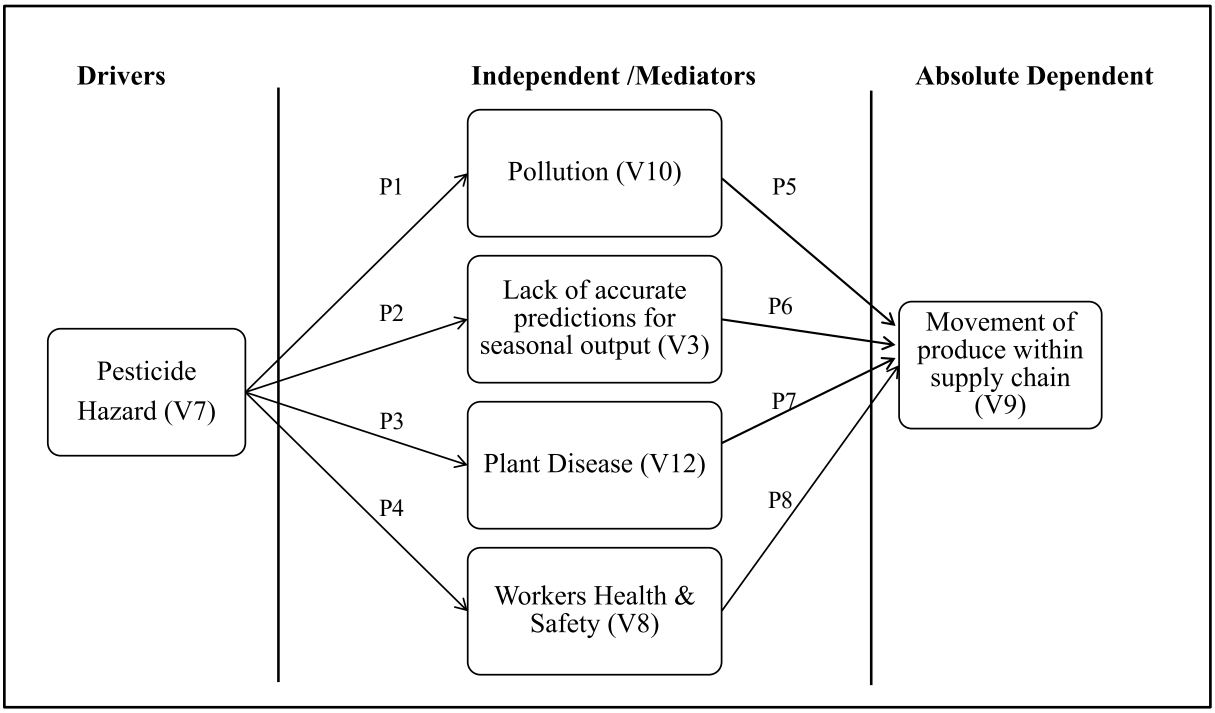

Fig. 7. Proposed model for the use of AI-Drone in CAP

Previous studies have uncovered the promise of I4.0 related technologies in reducing plant disease rates, such as IoT-based monitoring system (Khattab et al., 2019) as well as the role of drone sensors in helping minimising plant disease through earlier detection. More specifically, Stella et al. (2017) report how sensors can help identify apple scab infections, whilst also emphasising how the optimisation of pesticides is a priority and of high importance for farmers of the future. Sensors can help capture valuable data such as the temperature and moistness of soil leaf, level of precipitation, wind speed, as well as solar resource (Khattab et al., 2019), which may be vital in monitoring the condition of plants. While many studies have explored the potential of sensing techniques in detecting diseases and in monitoring crops (Mahlein et al., 2012; Spalević et al., 2018), the possibilities presented by drones have further increased the potential of such applications. Therefore, there is a need to explore whether through the application of drones, pesticides use can be minimised, which in turn can lead to healthier yield and overall the movement of more produce within the supply chain. Thus by utilising I4.0, there may be the potential of designing out waste and minimising pollution. Therefore, the following proposition is put forward:

Proposition 1: The effective and precise application of pesticides will significantly reduce plant disease and pollution.

Agricultural work conditions are often the subject of an ethical debate. While the literature on pesticides related health implications is well developed (Shammi et al. 2018; Bonner et al., 2017), more needs to be understood regarding approaches which can be taken to help reduce the health and safety risks farmers face through pesticides exposure. Traditionally, tracking workers for excessive exposure to pesticides is largely considered impractical, due to firstly monitoring tools being economically inaccessible and also due to protection from pesticides is largely associated with the use of personal protective equipment (PPE), which has its own set of challenges, particularly given the hot environments in which workers should apply them and that, in general, PPE is considered the least effective form of controls for workers (Keifer et al., 2010). There are also a shortfall of studies centred on farmers behaviours and in particular, their attitudes relating to pesticides use, as studies have previously indicated that farmers may still excessively spray pesticides, despite it being widely accepted that this may be detrimental to their health (Liu and Huang 2013). Accordingly, given the limited tools and techniques in minimising pesticide hazards, as well as lack of insight into the motivations behind farmers excessive use of pesticides, there is a need to explore whether through the application of drones, pesticides related hazards can significant be reduced, thus leading to healthier farmers and agricultural workers. Therefore, the following proposition is put forward:

Proposition 2: The application of pesticides through Precision I.40 Drones will significantly reduce workers health and safety challenges and lead to more produce in the Supply Chain.

The thermal imaging capability of the AI-drones helps the farmers to assess the health of their crops (Calderone, 2017). The "multi-spectral sensors" mounted on the drones allows a farmer to precisely apply pesticides – i.e. to target certain crops and apply certain quantity of pesticide only where and when it is needed, rather than applying a uniform amount of pesticide across the entire field. This practice does not just ensure the health of the crops but also the health of consumers. The excessive application of pesticides on crop would not just lead to various health issues to its consumer (Fuhrimann et al., 2019; Schreinemachers et al., 2020), but could also increase the operational cost unnecessarily – shrinking the farmer's margin of yield (Devkota et al., 2019). Moreover, Todorović et al. (2018) suggests any input towards crops could directly affects the yield, the farmer's income, as well as the environmental quality. Given these, the key to obtain and sustain a bigger margin of yield from the crops and ensure the production of 'healthy' crops for safe consumption lies in the precise application of the pesticides on the crops (Bhandari et al., 2018; Mie et al., 2017). Consumers may fear for their health to consume the agriculture produces in absence of precise measures and monitoring of the pesticide application (Margni et al., 2002). Jouzi et al. (2017) argued that the use of pesticide is one of the main reasons why consumer choose to consume organic produce rather than the non-organic. The change of consumer preference towards organic crops has subsequently caused the yield gained by the conventional non-organic crop farmers to dwindle. As the result, it can be asserted that application of the right quantity of pesticide to crops are key to CAP. Therefore, the following proposition is put forward:

Proposition 3: Precise pesticides application will lead to healthier crops and yield.

Healthier crops translates to better food production, therefore having significant impact on both the environment and those who consume from it. The crops output not just underscores the farmers yield (Todorović et al., 2018), but also guarantees the production of adequate output to ensure enough supply of food for the world's population (Dong et al., 2014). The output is determined by various intertwining factors, particularly the soil nutrients and fertilization (Dong et al., 2019). Fertilisation is a common yet precursor measure to ensures the crops are supplied with nutrients needed for growth by improving fertility of soil (Huang et al., 2017). However, the high input of fertilizer bring about environmental implications that are damaging to health, ecosystem and resources – calling for a sustainable agricultural practices via adoption of precision agriculture method (Todorović et al., 2018). This has become more serious concern as Parfitt et al. (2010) asserts that the urbanisation is expected to increase sharply with the expansion of global population to nine billion by 2050. The steady growth of global population with upward urbanisation trend would further cause instability in food supply chain (Srovnalíková and Ditkus, 2016). This, together with the demand for high variety and fast delivery of food with minimal costs require a more complex, cost-sensitive supply chain strategy (Gružauskas et al., 2019). An extra focus should be given to the "last-mile delivery" as it currently represents a significantly high cost in the whole supply chain, due to uncertainty and disturbances (de Souza et al., 2014), as well as inability to cope with disruptions (Managa et al., 2018). Gružauskas et al. (2019) propose that food supply chain collaboration can be improved by enhancing its collaborative technologies and strategies that could align demand and supply, reducing the uncertainty and disturbances. Forecasting of weather is one of the vital activities in farming, as it will help the farmers in daily decision makings, especially on crop irrigation and time to fertilize, which will result in a profitable crop or failure. The use of AI drones in agriculture would help to inform farmers ranges of data in timely and prompt manner. Therefore, the following proposition is put forward:

Proposition 4: AI drone will facilitate prediction of crop output that minimise uncertainty and disturbances in agricultural supply chain

Previous research indicates that the agriculture activities would account for up to 16% climate change in 2050, due to carbon emission and land degradation (Pinguet 2020). The situation calls for a change in farming practices – not just to reduce save the climate but also to protect the farmers against the economic loss in the aftermath. AI-drone, which is often used in the precision agricultural practices could partly mitigate this issue by cutting pollution in farming activities such as the use of light aircraft in seeding and pesticide application. The sensor attached to the drone allows farmers to precisely monitor the crops, allowing right amount of fertilisers or pesticides prescriptions at the right time, which helps the treatment while reducing environmental impact i.e. pollution due to the excessive use of such materials. A study by Canadian Government confirms that crops are vulnerable to death-leading "injury" when exposed to air pollutants (Ministry of Environment Canada, 2013), which would not only affect the growth of the crops and the farmers' yield, but threatens the supply in general. Therefore, the following proposition is put forward:

Proposition 5: Lack of pollution due to the use of AI drone lead to uninterrupted movement of produce in the supply chain

While the thermal imaging capability of the AI-drones assists farmers in evaluating crops conditions, (Calderone, 2017), the use of GPS and geospatial systems on drone (thus the drone is called the AI-Drone) allows farmers an access to a 'ready to use', real time, location-based data. This data informs the farmers of the potential yields or risks, thus could be used to perform intervention (Pinguet, 2020). Early intervention – for instance application of pesticide to curb the spread of the disease to other crops, is vital in ensuring the quantity harvest, which also underscores the security of movement in the supply chain – i.e. preventing 'break-down' of supply. Therefore, the following proposition is put forward :

Proposition 6: Accuracy of prediction due to the use of AI drone secures movement of the produce in the supply chain.

Another key challenge highlighted in this research is that of Plant diseases (V12). The extant literature also supports this, for instance, Mahlein et al. (2012) explore technology that detects plant diseases to precisely target the affected crop for protection, which utilise the multispectral, convoluted data. In the other hand, plant pathology, engineering, and informatics can be combined in a multi-disciplinary approach to screen fungicide and overcome the challenge of resistance breeding. Moreover, Khanal et al. (2017) also place emphasis in their study on the use of hyperspectral sensing to monitor crop stresses and diseases, as well as the irrigation stress. Thus highlighting the opportunities presented by I4.0 related technologies in overcoming traditional agricultural challenges, such as plant diseases. Therefore, the following proposition is put forward:

Proposition 7: Precision treatment of plant disease using AI drone facilitates smooth movement of the produce in the supply chain.

Workers health and safety has also been highlighted as a key challenge in this research (V8), and is also a key ethical challenge reported in previous studies. For example, in advocating the importance of working conditions for farmers and farm communities in light of ensuring food security, Lunner-Kolstrup and Ssali (2016) reveal a lack of awareness among the farmers particularly in developing country contexts, of health and safety issues, disease management, as well as knowledge on how to prevent injuries within agricultural settings. In addition to pesticides exposure, studies have also highlighted other worker health and safety factors prevalent within agriculture, such as fatigue, limited PPE, as well as oversight on the health and safety threats (Lunner-Kolstrup et al. 2016; Mitloehner and Calvo 2008). Thus, proactive efforts in overcoming such ethical issues can significantly improve working conditions, labour productivity and thus improve the movement of goods within supply chain settings (Lunner-Kolstrup and Ssali 20016). Therefore, the following proposition is put forward :

Proposition 8: Workers health and safety underpins the movement of goods within supply networks

7. Conclusion, limitations and future research

This research aimed to explore key challenges associated with agricultural supply chains, in doing so and more specifically, the research set out to identify how these key challenges influenced one another and what the relationships were between these challenges. Accordingly, this research reveals the underlying role of pesticide application and its associated health hazards, as being a key fundamental driver for many of the challenges faced within the supply chain. Moreover, the research also identified how pesticide application plays a role in influencing other factors within the supply chain, which ultimately, hinders cleaner agricultural production within the supply chains. This provides a potentially important precedent for agricultural stakeholders, such as farmers, policymakers, food producers, who are in the pursue of, or are currently engaged with cleaner agricultural practices. With this said, and in line with the extant literature, it is clear the role of pesticides and the concerns relating to its application and impact both on crops, and the workers who are exposed to it. Exploring this further through CE lenses and a review of I4.0 related literature, it is also identified that managing the application of this can be potentially achieved through the application of AI drones, thus leading to CAP, where resource-efficient agricultural practice is achieved through the reduction in fertilizer and pesticide use. Findings from this work can alert food producers and policymakers alike of the advantages and positive societal wide benefits of implementing I4.0 drones. In addition to pesticide use, agricultural stakeholders, through this research can help them identify, other associated challenges, which may also adversely impact their agricultural productivity. Not only are the findings suggestive of the economical and cost effectiveness resulting from reduced pesticides use, but they also allude to the wider reaching benefits of minimising the hazards associated with excessive pesticides use, on plants, livestock, humans and the environment as a whole. Ethics was also a focal aspect of this research, which has contributed further towards the academic discussion relating to, CE, its integration with I4.0 technologies, and how this can significantly role in mitigate ethical and socio-environment agricultural challenges.

This is about awareness of the CE concepts and knowledge on the potentials of I4.0 technologies. One of the main takeaways is to consider ethical issues at early stage of agricultural supply chain – i.e. the point of production through CE lens, and to propose innovative solutions in addressing them. The findings offer another avenue, through which, ethical considerations relating to existing approaches to farming can be re-evaluated, especially from the perspective of reducing environmental and health related impact. Accordingly, there is a pressing need for investment in technological advancements and training within agricultural settings, in order for the ethical and cleaner agricultural benefits to be fully realised.

Despite the fact that this research offers valuable insights into identifying the interrelating nature of challenges associated with cleaner agricultural production within agricultural supply chains, the key limitations of this research must be acknowledged. For instance, the parsimonious model developed through inputs from the experts and the literature is yet to be tested through empirical research. Moreover, although experts played a central role in developing the model, they were from a small sample size, therefore human biases and predilection can also be regarded as limitation of this research.

In summation, this research proposes a parsimonious model which can be tested by researchers in this field, to help them understand the extent to which, I4.0 drones can overcome agricultural challenges. It is therefore, proposed that further research is undertaken in order to complete the validation of the propositions developed from this research, and that too, across different setting, which will ultimately assist agricultural stakeholders in scenario building and action planning, towards successful implementation of an ethical, clean, agricultural production.

References

Abouziena, Hussein & Haggag, W.M. (2016). Weed Control in Clean Agriculture: A Review. Planta Daninha, 34, 377-392. 10.1590/S0100-83582016340200019.

Akkerman, R., Farahani, P, & Grunow, M. (2010). Quality, safety and sustainability in food distribution: A review of quantitative operations management approaches and challenges. OR Spectrum (2010) 32:863–904, DOI 10.1007/s00291-010-0223-2.

Alawneh, F., & Zhang, G. (2018). Dual-channel warehouse and inventory management with stochastic demand. Transportation Research Part E: Logistics and Transportation Review, 112, 84-106. doi:10.1016/j.tre.2017.12.012

Ampaire, E. L., Acosta, M., Huyer, S., Kigonya, R., Muchunguzi, P., Muna, R., & Jassogne, L. (2019;2020;). Gender in climate change, agriculture, and natural resource policies: Insights from East Africa. Climatic Change, 158(1), 43-60. doi:10.1007/s10584-019-02447-0

Appiah, M., Blay, D., Damnyag, L., Dwomoh, F.K., Pappinen, A., & Luukkanen, O. (2009). Dependence on forest resources and tropical deforestation in Ghana. Environment, Development & Sustainability, 11, 471–487. https://doi.org/10.1007/s10668-007-9125-0

Aschemann-Witzel, J., Hooge, D., Ilona E, Rohm, H., Normann, A., Bossle, M. B., Grønhøj, A., & Oostindjer, M. (2017). Key characteristics and success factors of supply chain initiatives tackling consumer-related food waste – A multiple case study. Journal of Cleaner Production, 155(2), 33-45. doi:10.1016/j.jclepro.2016.11.173

Asumadu-Sarkodie, S., & Owusu, P. A. (2017). The impact of energy, agriculture, macroeconomic and human-induced indicators on environmental pollution: Evidence from Ghana. Environmental Science and Pollution Research, 24(7), 6622-6633. doi:10.1007/s11356-016-8321-6

Audate, P. P., Fernandez, M. A., Cloutier, G., & Lebel, A. (2019). Scoping review of the impacts of urban agriculture on the determinants of health. BMC Public Health, 19(1), 672-672. doi:10.1186/s12889-019-6885-z

Bashir, M. A., Liu, J., Geng, Y., Wang, H., Pan, J., Zhang, D., Liu, H. (2020). Co-culture of rice and aquatic animals: An integrated system to achieve production and environmental sustainability. Journal of Cleaner Production, 249, 119310. doi:10.1016/j.jclepro.2019.119310

Bax, V., Francesconi, W., & Quintero, M., (2016). Spatial modeling of deforestation processes in the Central Peruvian Amazon. Journal of Nature Conservation 29, 79–88. https://doi.org/10.1016/j.jnc.2015.12.002

Bekchanov, M., & Mirzabaev, A. (2018). Circular economy of composting in Sri Lanka: Opportunities and challenges for reducing waste related pollution and improving soil health. Journal of Cleaner Production, 202, 1107-1119. doi:10.1016/j.jclepro.2018.08.186

Belaud, J., Prioux, N., Vialle, C., & Sablayrolles, C. (2019). Big data for agri-food 4.0: Application to sustainability management for by-products supply chain. Computers in Industry, 111, 41-50. doi:10.1016/j.compind.2019.06.006

Bhandari, G., Atreya, K., Yang, X., Fan, L., & Geissen, V. (2018). Factors affecting pesticide safety behaviour: The perceptions of nepalese farmers and retailers. Science of the Total Environment, 631-632, 1560-1571. doi:10.1016/j.scitotenv.2018.03.144

Bibby, L., & Dehe, B. (2018). Defining and assessing industry 4.0 maturity levels - case of the defence sector. Production Planning & Control, 29(12), 1030-1043. doi:10.1080/09537287.2018.1503355

Birat, J. P. (2015). Life-cycle assessment, resource efficiency and recycling. Metallurgical Research & Technology, 112(2), 2271-3646. https://doi.org/10.1051/metal/2015009

Bonneau, V & Copigneaux, B. (2017) Industry 4.0 in Agriculture: Focus on IoT Aspects, European Commission, 2017 IDATE; Laurent Probst and Bertrand Pedersen, PwC.

Bonner, M.R., Freeman, L.E., Hoppin, J.A., Koutros, S., Sandler, D.P., Lynch, C.F., Hines, C.J., Thomas, K., Blair, A., & Alavanja, M.C. (2017). Occupational exposure to pesticides and the incidence of lung Cancer in the agricultural health study. Environmental Health Perspective 125, 544–551.

Boyd, L. A., Ridout, C., O'Sullivan, D. M., Leach, J. E., & Leung, H. (2013;2012;). Plant–pathogen interactions: Disease resistance in modern agriculture. Trends in Genetics, 29(4), 233-240. doi:10.1016/j.tig.2012.10.011

Burton, R. (2012) Understanding Farmers' Aesthetic Preference for Tidy Agricultural Landscapes: A Bourdieusian Perspective, Landscape Research, 37:1, 51-71, DOI: 10.1080/01426397.2011.559311

Calderone, L., 2017. How Do Drones Help Farmers? | Agritechtomorrow. [online] Agritechtomorrow.com. Available at: https://www.agritechtomorrow.com/article/2017/08/how-do-drones-help-farmers/10153/> [Accessed 16 June 2020].

Castellani, V., Sala, S., & Mirabella, N. (2015). Beyond the throwaway society: A life cycle-based assessment of the environmental benefit of reuse. Integrated Environmental Assessment and Management, 11(3), 373-382. https://doi.org/10.1002/ieam.1614Chapman P.A. (2010) Reducing product losses in the food supply chain. In: Mena C, Stevens G (eds) Delivering performance in food supply chains. Woodhead Publishing Limited, Cambridge.

Chauhan, B. S. (2013). Effect of tillage systems, seeding rates, and herbicides on weed growth and grain yield in dry-seeded rice systems in the philippines. Crop Protection, 54, 244-250. doi:10.1016/j.cropro.2013.09.001

Choudhary, S., Raheja, N., Yadav, S., Sharma, A., Yamini, N., Raheja, S., Yadav, M., Kamboj, Amit., Sharma,. (2018). A review: Pesticide residue: Cause of many animal health problems. Journal Of Entomology And Zoology Studies. 6.

Clack, W. (2013). The extent of Stock Theft in South Africa. Clack Acta Criminol. South. African J. Criminol. 26, 2013.

Coale A. J and Hoover E,M (2015), *Population Growth and Economic Development*. Princeton University Press, Princeton, NJ

Collins, A. M., Haddaway, N. R., Macura, B., Thomas, J., Randall, N., Taylor, J. J., . . . Gilbert, A. (2019). What are the impacts of within-field farmland management practices on the flux of greenhouse gases from arable cropland in temperate regions? A systematic map protocol. Environmental Evidence, 8(1), 1-7. doi:10.1186/s13750-019-0182-2

de Souza, R., Goh, M., Lau, H., Ng, W., & Tan, P. (2014). Collaborative urban logistics – synchronizing the last mile a Singapore research perspective. Procedia - Social and Behavioral Sciences, 125, 422-431. doi:10.1016/j.sbspro.2014.01.1485 de Preneuf, F. (2020) Food Security And COVID-19. [online] World Bank. Available at: <https://www.worldbank.org/en/topic/agriculture/brief/food-security-and-covid-19> [Accessed 13 October 2020].

Devkota, K.P., Sudhir-Yadav, Khanda, C.M., Beebout, S.J., Mohapatra, B.K., Singleton, G.R., & Puskur, R. (2020). Assessing alternative crop establishment methods with a sustainability lens in rice production systems of Eastern India. Journal of Cleaner Production 244, 118835. https://doi.org/10.1016/j.jclepro.2019.118835

Dich, J., Zahm, S.H., Hanberg, A., & Adami, H.O. (1997). Pesticides and cancer. Cancer Causes Control 8, 420–443.

Diwate. S., Phuge. S., Mhatare. S., Yadav. J., Anap. V & Talathi. J (2018). An Economic Analysis of Rice Based Cropping Systems in Ratnagiri District of Maharashtra. Bulletin of Environment, Pharmacology and Life Sciences Bull. Env. Pharmacol. Life Sci., Vol 8 ©2018 Academy for Environment and Life Sciences, India

Dong, D., Wang, C., Van Zwieten, L., Wang, H., Jiang, P., Zhou, M., & Wu, W. (2019). An effective biochar-based slow-release fertilizer for reducing nitrogen loss in paddy fields. Journal of Soils and Sediments, doi:10.1007/s11368-019-02401-8

Driessen, C., & Heutinck, L. (2015). Cows desiring to be milked? Milking robots and the co-evolution of ethics and technology on Dutch dairy farms. Agriculture and Human Values, 32(1), 3–20. https://doi.org/10.1007/s10460-014-9515-5.

Devkota, M., Devkota, K. P., Acharya, S., & McDonald, A. J. (2019). Increasing profitability, yields and yield stability through sustainable crop establishment practices in the rice-wheat systems of nepal. Agricultural Systems, 173, 414-423. doi:10.1016/j.agsy.2019.03.022

Dwivedi, Y.K., Rana, N.P., Janssen, M., Lal, B., Williams, M.D. & Clement, M. (2017). An empirical validation of a unified model of electronic government adoption (UMEGA). Government Information Quarterly, 34(2), 211-230.

Eastwood, C. R., Chapman, D. F., & Paine, M. S. (2012). Networks of practice for co-construction of agricultural decision support systems: Case studies of precision dairy farms in Australia. Agricultural Systems, 108, 10–18.

Eastwood, C. R., Klerkx, L., & Nettle, R. (2017). Dynamics and distribution of public and private research and extension roles for technological innovation and diffusion: Case studies of the implementation and adaptation of precision farming technologies. Journal of Rural Studies, 49, 1–12. https://doi.org/10.1016/j.jrurstud.2016.11.008.

Emran, M. A., Moshiur, F. B., Tarek, M. A., Islam, M. M., Ritu, R. F., Khan, M. P., & Sumon, K. A. (2020). Use of pesticide by the vegetables farmers and occupational health hazards posed by pesticide application in mymensingh district. Research in Agriculture, Livestock and Fisheries, 7(1), 165-174. doi:10.3329/ralf.v7i1.46844

Erickson, B. J., Johannsen, C. J., Vorst, J. J., & Biehl, L. L. (2004). Using remote sensing to assess stand loss and defoliation in maize. Photogrammetric Engineering & Remote Sensing, 70(6), 717-722.

Fatorachian, H., & Kazemi, H. (2018). A critical investigation of Industry 4.0 in manufacturing: Theoretical operationalisation framework. Production Planning & Control, 1-12.

Frankelius, P., Norrman, C., and Johansen, K. (2017). Agricultural innovation and the role of institutions: lessons from the game of drones. Journal of Agricultural and Environmental Ethics 1–27. doi: 10.1007/s10806-017-9703-6

Fuhrimann, S., Winkler, M. S., Staudacher, P., Weiss, F. T., Stamm, C., Eggen, R. I. Mora, A. M. (2019). Exposure to pesticides and health effects on farm owners and workers from conventional and organic agricultural farms in Costa Rica: Protocol for a cross-sectional study. JMIR Research Protocols, 8(1), e10914. doi:10.2196/10914

Gallenti, G., Troiano, S., Marangon, F., Bogoni, P., Campisi, B., & Cosmina, M. (2019). Environmentally sustainable versus aesthetic values motivating millennials' preferences for wine purchasing: Evidence from an experimental analysis in Italy. Agricultural and Food Economics, 7(1), 1-16. doi:10.1186/s40100-019-0132-x

Geissdoerfer, M., Savaget, P., Bocken, N., & Hultink, E. (2017). The Circular Economy – A new sustainability paradigm?. Journal of Cleaner Production, 143(1), 757-768. https://doi.org/10.1016/j.jclepro.2016.12.048

Gilligan, C. A. (2008). Sustainable agriculture and plant diseases: An epidemiological perspective. Philosophical Transactions of the Royal Society B: Biological Sciences, 363(1492), 741-759. doi:10.1098/rstb.2007.2181

Gnauer, C., Pichler, H., Tauber, M., Schmittner, C., Christl, K., Knapitsch, J., & Parapatits, M. (2019). Towards a secure and self-adapting smart indoor farming framework. Elektrotechnik Und Informationstechnik, 136(7), 341-344. doi:10.1007/s00502-019-00745-0

Gopal, P. R. C., & Thakkar, J. (2016). Analysing critical success factors to implement sustainable supply chain practices in Indian automobile industry: A case study. Production Planning & Control, 27(12), 1005-1018. doi:10.1080/09537287.2016.1173247

Gružauskas, V., Gimžauskienė, E., & Navickas, V. (2019). Forecasting accuracy influence on logistics clusters activities: The case of the food industry. Journal of Cleaner Production, 240, 118225. doi:10.1016/j.jclepro.2019.118225

Hahn, M.B., Gangnon, R.E., Barcellos, C., Asner, G.P., & Patz, J.A. (2014). Influence of deforestation, logging, and fire on malaria in the Brazilian Amazon. PLoS One 9. https://doi.org/10.1371/journal.pone.0085725

Hendrickson, M. K., & James, H. S. (2005). The ethics of constrained choice: How the industrialization of agriculture impacts farming and farmer behavior. Journal of Agricultural and Environmental Ethics, 18(3), 269-291.

Higgins, A., McFallan, S., Marinoni, O., McKeown, A., Bruce, C., Chilcott, C., & Pinkard, L. (2018). Informing transport infrastructure investments using TraNSIT: A case study for Australian agriculture and forestry. Computers and Electronics in Agriculture, 154, 187-203. doi:10.1016/j.compag.2018.09.008

Hillel D, Braimoh AK & Vlek PL (2008) Soil degradation under irrigation, in Land Use and Soil Resources, ed. by Ademola K Braimoh, Paul LG Vlek. Springer, Dordrecht, pp. 101–119

Hobson, K. (2016). Closing the loop or squaring the circle ? Locating generative spaces for the circular economy. Prog. Hum. Geogr. 40 (1), 88e104. https://doi.org/10.1177/0309132514566342.

Hofmann, E., & Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. Computers in Industry, 89, 23-34. doi:10.1016/j.compind.2017.04.002

Huang, J., Xu, C. chun, Ridoutt, B.G., Wang, X. C., & Ren, P. (2017). Nitrogen and phosphorus losses and eutrophication potential associated with fertilizer application to cropland in China. J. Clean. Prod. 159, 171–179. https://doi.org/10.1016/j.jclepro.2017.05.008

Hughes, D.L., Dwivedi, Y.K., Rana, N.P. & Simintiras, A.C. (2016). Information systems project failure – analysis of causal links using interpretive structural modelling. Production Planning & Control, 27(16), 1313-1333.

Jha, K., Doshi, A., Patel, P., & Shah, M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. Artificial Intelligence in Agriculture, 2, 1-12. doi:10.1016/j.aiia.2019.05.004

Jouzi, Z., Azadi, H., Taheri, F., Zarafshani, K., Gebrehiwot, K., Van Passel, S., & Lebailly, P. (2017). Organic farming and small-scale farmers: Main opportunities and challenges. Ecological Economics, 132, 144-154. doi:10.1016/j.ecolecon.2016.10.016

Kang, H. S., Lee, J. Y., Choi, S., Kim, H., Park, J. H., Son, J. Y., et al. (2016). Smart manufacturing: Past research, present findings, and future directions. International Journal of Precision Engineering and Manufacturing-Green Technology, 3(1), 111–128.

Karanja, A. W., Njeru, E. M., & Maingi, J. M. (2019). Assessment of physicochemical changes during composting rice straw with chicken and donkey manure. International Journal of Recycling of Organic Waste in Agriculture, 8(S1), 65-72. doi:10.1007/s40093-019-0270-x

Keifer, M., Gasperini, F., & Robson, M. (2010). Pesticides and other chemicals: Minimizing worker exposures. Journal of Agromedicine: Be Safe, be Profitable: Protecting Workers in Agriculture, 15(3), 264-274. doi:10.1080/1059924X.2010.486686

Khanal, S., Fulton, J., & Shearer, S. (2017). An overview of current and potential applications of thermal remote sensing in precision agriculture. Computers and Electronics in Agriculture, 139, 22-32. doi:10.1016/j.compag.2017.05.001

Khattab, A., Habib, S. E. D., Ismail, H., Zayan, S., Fahmy, Y., & Khairy, M. M. (2019). An IoT-based cognitive monitoring system for early plant disease forecast. Computers and Electronics in Agriculture, 166, 105028. doi:10.1016/j.compag.2019.105028

Lezoche, M., Hernandez, J. E., Alemany Díaz, Maria del Mar Eva, Panetto, H., & Kacprzyk, J. (2020). Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture. Computers in Industry, 117, 103187.doi:10.1016/j.compind.2020.103187.

Lindblom, J., Lundström, C., Ljung, M., Jonsson, A., Institutionen för informationsteknologi, Forskningscentrum för Informationsteknologi, & Högskolan i Skövde. (2017). Promoting sustainable intensification in precision agriculture: Review of decision support systems development and strategies. Precision Agriculture, 18(3), 309-331. doi:10.1007/s11119-016-9491-4

Liu, E.M & Huang, J. (2013) Risk preferences and pesticide use by cotton farmers in China, Journal of Development Economics 103, 202–215,

Lopes de Sousa Jabbour, A. B., Jabbour, C. J. C., Godinho Filho, M., & Roubaud, D. (2018). Industry 4.0 and the circular economy: A proposed research agenda and original roadmap for sustainable operations. Annals of Operations Research, 270(1-2), 273-286. doi:10.1007/s10479-018-2772-8

Lubberink, R., Blok, V., van Ophem, J., & Mota, O. (2017). Lessons for responsible innovation in the business context: A systematic literature review of responsible, social and sustainable innovation practise. Sustainability, 9(721), 1–31.

Lunner-Kolstrup, C., & Ssali, T. K. (2016). Awareness and need for knowledge of health and safety among dairy farmers interviewed in Uganda. Frontiers in Public Health, 4, 1-10. doi:10.3389/fpubh.2016.00137

Luthra, S., Kumar, S., Kharb, R., Ansari, M.F. and Shimmi, S.L. (2014), "Adoption of smart grid technologies: an analysis of interactions among barriers", Renewable and Sustainable Energy Reviews, 33, 554-565.

MacArthur and Waughray (2016) Intelligent Assets: Unlocking the circular economy potential, finds that "pairing circular economy principles. Rapport de la foundation. Ellen MacArthur

Mahlein, A., Mahlein, A., Oerke, E., Oerke, E., Steiner, U., Steiner, U., Dehne, H. (2012). Recent advances in sensing plant diseases for precision crop protection. European Journal of Plant Pathology, 133(1), 197-209. doi:10.1007/s10658-011-9878-z

Managa, M. G., Tinyani, P. P., Senyolo, G. M., Soundy, P., Sultanbawa, Y., & Sivakumar, D. (2018). Impact of transportation, storage, and retail shelf conditions on lettuce quality and phytonutrients losses in the supply chain. Food Science & Nutrition, 6(6), 1527-1536. doi:10.1002/fsn3.685

Mangla, S. K., Luthra, S., Mishra, N., Singh, A., Rana, N. P., Dora, M., & Dwivedi, Y. (2018). Barriers to effective circular supply chain management in a developing country context. Production Planning & Control: Supply Chain Operations for a Circular Economy, 29(6), 551-569. doi:10.1080/09537287.2018.1449265

Margni, M., Rossier, D., Crettaz, P., & Jolliet, O. (2002). Life cycle impact assessment of pesticides on human health and ecosystems. Agriculture, Ecosystems and Environment, 93(1), 379-392. doi:10.1016/S0167-8809(01)00336-X

Martin, W. (2018). Agriculture, structural transformation and poverty reduction: Eight new insights. World Development, 109, 413-416. doi:10.1016/j.worlddev.2018.05.027

Mastos, T. D., Nizamis, A., Vafeiadis, T., Alexopoulos, N., Ntinas, C., Gkortzis, D., Tzovaras, D. (2020). Industry 4.0 sustainable supply chains: An application of an IoT enabled scrap metal management solution. Journal of Cleaner Production, 269, 122377. doi:10.1016/j.jclepro.2020.122377

Mazur, M. (2016). Six ways drones are revolutionizing agriculture. MIT Technology Review.

Meijboom, F. L. B., & Brom, F. W. A. (2012). Ethics and sustainability: Guest or guide? on sustainability as a moral ideal. Journal of Agricultural and Environmental Ethics, 25(2), 117-121. doi:10.1007/s10806-011-9322-6

Mie, A., Andersen, H. R., Gunnarsson, S., Kahl, J., Kesse-Guyot, E., Rembiałkowska, E., . . . Grandjean, P. (2017). Human health implications of organic food and organic agriculture:

A comprehensive review. Environmental Health, 16(1), 111-122. doi:10.1186/s12940-017-0315-4

Mitloehner, F.M., & Calvo, M.S. (2008). Worker health and safety in concentrated animal feeding operations. J Agric Saf Health,14(2), 163-187. doi:10.13031/2013.24349

Millar, K. M. (2000). Respect for animal autonomy in bioethical analysis: The case of Automatic Milking Systems (AMS). Journal of Agricultural and Environmental Ethics, 12(1), 41–50.

Ministry of Environment Canada, 2013. *Effects Of Air Pollution On Agricultural Crops*. [online] Available at: <http://www.omafra.gov.on.ca/english/crops/facts/01-015.htm#:~:text=Introduction,premature%20death%20of%20the%20plant.> [Accessed 21 June 2020].

Miranda, J., Ponce, P., Molina, A., & Wright, P. (2019). Sensing, smart and sustainable technologies for agri-food 4.0. Computers in Industry, 108, 21-36. doi:10.1016/j.compind.2019.02.002

Moeuf, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S., & Barbaray, R. (2018). The industrial management of SMEs in the era of Industry 4.0. International Journal of Production Research, 56(3), 1118–1136.

Murray, A., Skene, K., & Haynes, K. (2015;2017;). The circular economy: An interdisciplinary exploration of the concept and application in a global context. Journal of Business Ethics, 140(3), 369-380. doi:10.1007/s10551-015-2693-2

Naik, G., & Suresh, D.N. (2018). Challenges of creating sustainable agri-retail supply chains. IIMB Management Review, 30(3), 270-282. doi:10.1016/j.iimb.2018.04.001

Nazeer, M., Tabassum, U., & Alam, S. (2016). Environmental pollution and sustainable development in developing countries. The Pakistan Development Review, 55(4), 589-604. doi:10.30541/v55i4I-IIpp.589-604

Okumah, M., Chapman, P. J., Martin-Ortega, J., & Novo, P. (2018). Mitigating agricultural diffuse pollution: Uncovering the evidence base of the awareness-behaviour-water quality pathway. Water (Switzerland), 11(1), 29. doi:10.3390/w11010029

Panetto, H., Lezoche, M., Hernandez Hormazabal, J. E., del Mar Eva Alemany Diaz, Maria, & Kacprzyk, J. (2020). Special issue on agri-food 4.0 and digitalization in agriculture supply chains - new directions, challenges and applications. Computers in Industry, 116, 103188. doi:10.1016/j.compind.2020.103188

Parfitt, J., Barthel, M., & Macnaughton, S. (2010). Food waste within food supply chains: Quantification and potential for change to 2050. Philosophical Transactions: Biological Sciences, 365(1554), 3065-3081. doi:10.1098/rstb.2010.0126

Patwa, N., Sivarajah, U., Seetharaman, A., Sarkar, S., Maiti, K., & Hingorani, K. (2020). Towards a circular economy: An emerging economies context. Journal of Business Research, doi:10.1016/j.jbusres.2020.05.015

Pauliuk, S., 2018. Resources, conservation & recycling critical appraisal of the circular economy standard BS 8001 : 2017 and a dashboard of quantitative system indicators for its implementation in organizations. Resour. Conserv. Recyc. 129 (September 2017), 81e92. https://doi.org/10.1016/j.resconrec.2017.10.019. Elsevier.

Peng, Y., Peng, Z., Zeng, X., & Houx III, J. H. (2019). Effects of nitrogen-phosphorus imbalance on plant biomass production: A global perspective. Plant and Soil, 436(1), 245-252. doi:10.1007/s11104-018-03927-5

Pinguet, B., 2020. *The Role Of Drone Technology In Sustainable Agriculture*. [online] Precisionag.com. Available at: <https://www.precisionag.com/in-field-technologies/drones-uavs/the-role-of-drone-technology-in-sustainable-agriculture/> [Accessed 21 June 2020].

Qin, G., Tao, F., & Li, L. (2019). A vehicle routing optimization problem for cold chain logistics considering customer satisfaction and carbon emissions. International Journal of Environmental Research and Public Health, 16(4), 576. doi:10.3390/ijerph16040576

Rahaman, M. M., & Varis, O. (2005). Integrated water resources management: Evolution, prospects and future challenges. Sustainability: Science, Practice and Policy, 1(1), 15-21. doi:10.1080/15487733.2005.11907961

Rajao, R., Soares-Filho, B., Nunes, F., Borner, J., Machado, L., Assis, D., . Figueira, D. (2020). The rotten apples of brazil's agribusiness: Brazil's inability to tackle illegal deforestation puts the future of its agribusiness at risk. Science (American Association for the Advancement of Science), 369(6501), 246. doi:10.1126/science.aba6646

Rana, N. P., Barnard, D. J., Baabdullah, A. M. A., Rees, D., & Roderick, S. (2019a). Exploring barriers of m-commerce adoption in SMEs in the UK: Developing a framework using ISM. International Journal of Information Management, 44, 141-153. doi:10.1016/j.ijinfomgt.2018.10.009

Rana, N. P., Luthra, S., & Rao, H. R. (2019b) Key challenges to digital financial services in emerging economies: The Indian context. Information Technology & People, 33(1), 198-229. doi:10.1108/ITP-05-2018-0243

Reger, M., Bauerdick, J., & Bernhardt, H. (2018). Drones in agriculture: Current and future legal status in Germany, the EU, the USA and Japan. Landtechnik, 73(3) doi:10.15150/lt.2018.3183

Rodale Institute (2014) Rodaleinstitute.org. [online] Available at: <https://rodaleinstitute.org/wp-content/uploads/rodale-white-paper.pdf> (Accessed 27 June 2020)

Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0: Broadening responsible innovation in an era of smart farming. Frontiers in Sustainable Food Systems, 2 doi:10.3389/fsufs.2018.00087

Rushton A., Croucher P., & Baker P (2006). The Handbook of Logistics and Distribution Management, 3rd Edn. Kogan Page, London, UK

Sauvé, S., Bernard, S., & Sloan, P. (2016). Environmental sciences, sustainable development and circular economy: Alternative concepts for trans-disciplinary research. Environmental Development, 17, 48-56. doi:10.1016/j.envdev.2015.09.002

Scupola, A., & Zanfei, A. (2016). Governance and innovation in public sector services: The case of the digital library. Gov. Inf. Q. 33, 237–249. https://doi.org/10.1016/j.giq.2016.04.005

Schreinemachers, P., Balasubramaniam, S., Boopathi, N. M., Ha, C. V., Kenyon, L., Praneetvatakul, S., . . . Wu, M. (2015). Farmers' perceptions and management of plant viruses in vegetables and legumes in tropical and subtropical Asia. Crop Protection, 75, 115-123. doi:10.1016/j.cropro.2015.05.012

Shammi, M., Sultana, A., Hasan, N., Mostafizur Rahman, M., Saiful Islam, M., Bodrud-Doza, M., & Khabir Uddin, M. (2018). Pesticide exposures towards health and environmental hazard in Bangladesh: A case study on farmers' perception. Journal of the Saudi Society of Agricultural Sciences, 19(2), 161-173. doi:10.1016/j.jssas.2018.08.005

Sharifzadeh, M. S., Abdollahzadeh, G., Damalas, C. A., Rezaei, R., & Ahmadyousefi, M. (2019). Determinants of pesticide safety behavior among iranian rice farmers. The Science of the Total Environment, 651(Pt 2), 2953-2960. doi:10.1016/j.scitotenv.2018.10.179

Shiva, V. (2016). The Violence of the Green Revolution: Third World Agriculture, Ecology, and Politics. University Press of Kentucky, Lexington, KY.

Smith, B.G. (2008). Developing sustainable food supply chains. Philosophical Transactions of the Royal Society B: Biological Sciences, 363(1492), 849–861.

Sousa-Zomer, T. T., Magalhães, L., Zancul, E., Campos, L .M., & Cauchick-Miguel, P. A. (2018). Cleaner production as an antecedent for circular economy paradigm shift at the micro-level: Evidence from a home appliance manufacturer. Journal of Cleaner Production, 185, 740-748. https://doi.org/10.1016/j.jclepro.2018.03.006

Spalević, Ž., Ilić, M., & Savija, V. (2018). The use of drones in agriculture: ICT policy, legal and economical aspects. Ekonomika, 64(4), 93-107. doi:10.5937/ekonomika1804091S

Sruthi, S. N., Sruthi, S. N., Shyleshchandran, M. S., Shyleshchandran, M. S., Mathew, S. P., Mathew, S. P., Ramasamy, E. V. (2017). Contamination from organochlorine pesticides (OCPs) in agricultural soils of kuttanad agroecosystem in india and related potential health risk. Environmental Science and Pollution Research International, 24(1), 969-978. doi:10.1007/s11356-016-7834-3#

Stella, A., Caliendo, G., Melgani, F., Goller, R., Barazzuol, M., & La Porta, N. (2017). Leaf wetness evaluation using artificial neural network for improving apple scab fight. Environments, 4(2), 42. doi:10.3390/environments4020042

Strassburg, B. B. N., Latawiec, A., & Balmford, A. (2016). Brazil: Urgent action on cerrado extinctions. Nature (London), 540(7632), 199. doi:10.1038/540199a

Stock, T., & Seliger, G. (2016). Opportunities of sustainable manufacturing in Industry 4.0. Procedia Cirp, 40, 536–541.

Stuthman, D. D., Leonard, K. J., & Miller-Garvin, J. (2007). Breeding crops for durable resistance to disease. Advances in Agronomy, 95, 319–367.

Su, B., Heshmati, A., Geng, Y., & Yu, X. (2013). A review of the circular economy in china: Moving from rhetoric to implementation. Journal of Cleaner Production, 42, 215-227. doi:10.1016/j.jclepro.2012.11.020

Suárez-Eiroa, B., Fernández, E., Méndez-Martínez, G., & Soto-Oñate, D. (2019). Operational principles of circular economy for sustainable development: Linking theory and practice. Journal of Cleaner Production, 214, 952-961. doi:10.1016/j.jclepro.2018.12.271

Sundström, J. F., Albihn, A., Boqvist, S., Ljungvall, K., Marstorp, H., Martiin, C., Magnusson, U. (2014). Future threats to agricultural food production posed by environmental degradation, climate change, and animal and plant diseases – a risk analysis in three economic and climate settings. Food Security, 6(2), 201-215. doi:10.1007/s12571-014-0331-y

Talbot, B., Rahlf, J., & Astrup, R. (2018). An operational UAV-based approach for stand-level assessment of soil disturbance after forest harvesting. Scandinavian Journal of Forest Research, 33(4), 387-396. doi:10.1080/02827581.2017.1418421

Tantalaki, N., Souravlas, S., Roumeliotis, M. (2019). Data-Driven Decision Making in Precision Agriculture: The Rise of Big Data in Agricultural Systems. Journal of Agricultural and Food Information, 20, 344–380. https://doi.org/10.1080/10496505.2019.1638264

Todorović, M., Mehmeti, A., Cantore, V., 2018. Impact of different water and nitrogen inputs on the eco-efficiency of durum wheat cultivation in Mediterranean environments. Journal of Cleaner Production 183, 1276–1288. https://doi.org/10.1016/j.jclepro.2018.02.200

Toop, T.A., Ward, S., Oldfield, T., Hull, M., Kirby, M.E., Theodorou, M.K., 2017. AgroCycle - Developing a circular economy in agriculture, in: Energy Procedia. Elsevier Ltd, pp. 76–80. https://doi.org/10.1016/j.egypro.2017.07.269

Trentesaux, D., Borangiu, T., & Thomas, A. (2016). Emerging ICT concepts for smart, safe and sustainable industrial systems. Computers in Industry, 81, 1–10.

United Nations Department of Economic and Social Affairs. World population projected to reach 9.7 billion by 2050. 2015; [Online]. Available: http://www.un.org/en/development/desa/news/population/2015-report.html. [Accessed 04 June 2020].

Van der Burg, S., Bogaardt, M., & Wolfert, S. (2019). Ethics of smart farming: Current questions and directions for responsible innovation towards the future. NJAS - Wageningen Journal of Life Sciences, 90-91, 100289. doi:10.1016/j.njas.2019.01.001

Vasconez, J. P., Kantor, G. A., & Auat Cheein, F. A. (2019). Human–robot interaction in agriculture: A survey and current challenges. Biosystems Engineering, 179, 35-48. doi:10.1016/j.biosystemseng.2018.12.005

Waibel, M. W., Steenkamp, L. P., Moloko, N., & Oosthuizen, G. A. (2017). Investigating the effects of smart production systems on sustainability elements. Procedia Manufacturing, 8, 731–737.

Walker, R., Moran, E., & Anselin, L. (2000). Deforestation and Cattle Ranching in the Brazilian Amazon: External Capital and Household Processes. World Development 28, 683–699.

Warfield, J.N. (1974), “Developing interconnected matrices in structural modeling”, IEEE Transactions on Systems, Man and Cybernetics, Vol. 4 No. 1, pp. 51-81.

WHO International (2018). Pesticide residues in food. [online] Available at: https://www.who.int/news-room/fact-sheets/detail/pesticide-residues-in-food [Accessed 23 Feb. 2020].

Winans, K., Kendall, A., & Deng, H. (2017). The history and current applications of the circular economy concept. Renewable and Sustainable Energy Reviews, 68, 825-833. https://doi.org/10.1016/j.rser.2016.09.123

Wolf, S. A., & Wood, S. D. (1997). Precision farming: Environmental legitimation, commodification of information, and industrial Coordination1. Rural Sociology, 62(2), 180-206. doi:10.1111/j.1549-0831.1997.tb00650.x

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. (2017). Big data in smart farming – A review. Agricultural Systems, 153, 69-80. doi:10.1016/j.agsy.2017.01.023

Wognum, P.M., Bremmers, H., Trienekens, J.H., Van der Vorst, J.G.A.J., Bloemhof, J.M. (2010). Systems for sustainability and transparency of food chains—current status and challenges. Adv Eng Inform (in press). doi:10.1016/j.aei.2010.06.001

Yadav, G., Luthra, S., Jakhar, S. K., Mangla, S. K., & Rai, D. P. (2020). A framework to overcome sustainable supply chain challenges through solution measures of industry 4.0 and circular economy: An automotive case. Journal of Cleaner Production, 254, 120112. doi:10.1016/j.jclepro.2020.120112

Yost, M. A., Yost, M. A., Sudduth, K. A., Sudduth, K. A., Walthall, C. L., Walthall, C. L., Kitchen, N. R. (2019). Public–private collaboration toward research, education and innovation opportunities in precision agriculture. Precision Agriculture, 20(1), 4-18. doi:10.1007/s11119-018-9583-4

Young, S. (2020). the future of farming artificial intelligence and agriculture. Harvard International Review, 41(1), 45.

Zhang C. H., & Kovacs J. M. (2012). The application of small unmanned aerial systems for precision agriculture: A review. Precision Agriculture, 13(6), 693–712. 10.1007/s11119-012-9274-5

Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of Industry 4.0: A review. Engineering, 3(5), 616–630.