EXPLORING LEAN & GREEN INTERNET OF THINGS (IOT) WIRELESS SENSORS FRAMEWORK FOR THE ADOPTION OF PRECISION AGRICULTURE PRACTICES AMONG INDIANA ROW-CROP PRODUCERS

by

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To my family

Thank you, Dad and Mom, for always believing in me and standing by me in good and bad times

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GLOSSARY

1. Lean-Green drivers – relates to Delivery performance, Profitability, Overall productivity, Hazardous waste reduction, Operational cost, Information sharing and Employee satisfaction (Thanki & Thakkar. 2018; Gandhi, Thanki & Thakkar. 2018).

2. Precision Agriculture Technologies- Precision agriculture is “a management strategy that uses information technology to bring data from multiple sources to bear on decisions associated with crop production”. Precision agriculture tools include information gathering tools such as yield monitors, targeted soil sampling and remote sensing tools; variable rate technology; guidance systems such as light bars and auto steer equipment (Bongiovanni & Lowenberg-DeBoer, 2004).

3. Internet of Things (IoT) framework- Consists of four layers namely 1. Perception layer (Sensors) 2. Communication layer (Wireless communication technologies) 3. Processing layer (Data storage & processing layer) 4. Application Layer (Jawad, Nordin, Gharghan & Ismail, 2017).

4. Application programming interface (API’s)- Computing interface which defines interactions between multiple software intermediaries consisting of a set of functions and procedures allowing the creation of user applications (monitoring row crop diseases, smart irrigation, smart fertilizing, and farm-machinery efficient navigation) in the context of precision agriculture.

5. Row crops- A row crop is a crop that can be planted in rows wide enough to allow it to be tilled or otherwise cultivated by agriculture machinery, machinery tailored for the seasonal activities of row crops. Corn and soybean are the major row crops grow in Indiana region

6. Interpretive Structural Modeling- is a technique to develop a theoretical framework model from interpretive matrix analysis performed over content analysis of interview data.

LIST OF ABBREVIATIONS

BV- Battery Voltage

CR- Communication Range

CT – Cost

DI- Data Interoperability

DP- Data processing

DS – Data Storage

DL – Data Latency

DSC – Data Scalability

IoT – Internet of Things

ISM – Interpretive Structural Modeling

LORAWAN- Low Power Wide Area Network

USDA– United States Department of Agriculture

PC – Power Consumption

RSSI- Received Signal Strength Index

SNR- Signal to Noise Ratio

TPA– Type of Precision Application

TS- Type of Sensor

TWC – Type of Wireless Communication

WSN- Wireless Sensors Network

ABSTRACT

The production of row crops in the Midwestern (Indiana) region of the US has been facing environmental and economic sustainability issues. There has been an increase in trend for the application of fertilizers (Nitrogen & Phosphorus), farm machinery fuel costs and decrease in labor productivity leading to non-optimized usage of farm-inputs. A structured literature review describes Lean and Green practices such as profitability (return on investments), operational cost reduction, hazardous waste reduction, delivery performance and overall productivity might be adopted in the context of Precision Agriculture practices (variable rate irrigation, variable rate fertilization, cloud-based analytics, and telematics for farm-machinery navigation).

The literature review describes low adoption of Internet of Things (IoT) based precision agriculture practices, such as variable rate fertilizer (39 %), variable rate pesticide (8%), variable rate irrigation (4 %), cloud-based data analytics (21 %) and telematics (10 %) amongst Midwestern row crop producers. Barriers for the adoption of IoT based Precision Agriculture practices include cost effectiveness, power requirements, communication range, data latency, data scalability, data storage, data processing and data interoperability. Focused group interviews (n=3) with Subject Matter Expertise (SME's) (N=18) in IoT based Precision Agriculture practices were conducted to understand and define decision-making variables related to barriers. The content analysis and subsequent ISM model informed an action research approach in the deployment of an IoT wireless sensor nodes for performance improvement. The improvements resulted in variable cost reduction by 94 %, power consumption cost reduction by 60 %, and improved data interoperable and user-interactive IoT wireless sensor-based data pipeline for improved adoption of Precision Agriculture practices. A relationship analysis of performance data (n=2505) from the IoT sensor deployment empirically validated the ISM model and explained the variation in power consumption for mitigation of IoT adoption among producers. The scope of future research for predicting IoT power consumption, based upon the growing season through correlation was developed in this study.

The implications of this research inform adopters (row-crop producers), researchers and precision agriculture practitioners that a Lean and Green framework is driven substantively by cost and power concerns in an IoT sensors-based precision agriculture solution.

CHAPTER 1. INTRODUCTION

1.1 Introduction

Row crops corn and soybean production in the Midwestern US region has economic and environmental concerns, based on an increase trend in the application of nitrogen and phosphorous fertilizers (USDA NASS Indiana, 2019). Operational costs and fuel consumption costs have increased with a decrease in labor productivity and resulted in lower net farm income (USDA NASS Indiana, 2019). As a result, Lean and Green practices such as profitability (return on investments), operational cost reduction, hazardous waste reduction, delivery performance and overall productivity might be adopted through adoption of precision agriculture applications (variable rate irrigation, variable rate fertilization, cloud-based analytics, and telematics for farm-machinery navigation) to improve agriculture operations and net profitability. However, DeBoer & Erickson., (2019) note the low rate of adoption for variable rate fertilizer (39 %), variable rate pesticide (8 %), variable rate irrigation (4 %), cloud-based data analytics (21 %) and telematics (10 %) amongst Midwestern US row crop producers. These barriers include operational costs, power consumption requirements, communication range limitations, data latency, data scalability, data storage, data processing and data interoperability and are highlighted in the literature (Jawad et al. 2017; Ruan et al., 2019). This thesis explores and defines the relationships among decision making variables related to barriers for adoption of IoT based precision agriculture practices, utilizing focused group interviews (n=3) with SME's (N= 18). These SME's include digital agriculture practitioners (farmers), and specialist in wireless communication technology. A content analysis of SME feedback was conducted to develop a theoretical framework using Interpretive Structural Modeling. This theoretical framework informed the actions of the researchers in IoT sensors test beds at Purdue University to empirically validate the framework. The implications of this research fill a knowledge gap among stakeholders (Indiana row-crop producers, Precision Agriculture Technologists, Digital Agriculture practitioners) that subscribe to Lean- Green practices through the adoption and deployment of IoT wireless sensors-based precision agriculture practices.

1.2 Problem Statement

The production of row crops in the Midwestern region of the US has been facing growing environmental and economic sustainability issues. From the perspective of economic sustainability performance there has been an increase in total operational cost, including fuel expenses, with a subsequent decrease in labor productivity and net farm income. The impact of non-optimized usage of inputs especially fertilizers, pesticides, labor, and farm machinery has led to an increase in operational costs with little increase in yields and net farm income (USDA NASS, 2019). Lean and green practices i.e., profitability (return on investments), operational cost reduction, hazardous waste reduction, delivery performance and overall productivity may be adopted by producers in the context of precision agriculture applications such as smart irrigation, smart fertilization, monitoring row crop diseases and farm machinery navigation to improve yields and reduce costs (Fountas et al. 2005; Schimmelpfennig. D. 2016; Say et al. 2018). Still, there is highlights low rate of adoption for Internet of Things based Precision Agriculture practices among the Midwest row crop producers (DeBoer & Erickson., 2019). Barriers to adoption include operational costs, power consumption requirements, communication range limitations, data latency, data scalability, data storage, data processing and data interoperability (Jawad et al. 2017; Ruan et al., 2019). Therefore, this research understands the barriers to IoT for a Lean & Green approach.

1.3 Scope

The scope of this study explores Lean and Green practices through the lens of Internet of Things (IoT) wireless sensors-based precision agriculture technologies amongst row crop producers in the Midwestern (Indiana) region for robust economic and environmental sustainability performance. The scope of structured literature review conducted in this study is limited to the Midwest (Indiana) geographical region of the US. The research focuses on answering the current adoption and understanding of issues based upon IoT wireless sensors-based precision agriculture technologies (Smart Irrigation, Smart fertilization, Monitoring row crop diseases and Farm machinery navigation) for the adoption and deployment for Lean and Green agricultural production. The findings and outcomes focus on filling knowledge gaps, based on decision variables involved in IoT wireless sensors-based data pipeline and the relationship amongst each variable through Interpretive Structural Modeling (ISM). This thesis also recommends solutions focused on lean-green adoption through IoT wireless sensors-based precision agriculture application, and comparison of action research deployments and empirical testing of the ISM framework model.

1.4 Significance

The research findings fill a knowledge gap in understanding the barriers to decision making of adopting an IoT precision agriculture system among row crop producers. The ISM model describes the relationships among the practical decision making is significant in IoT wireless sensors-based data pipeline deployment. Purdue Agronomy Center for Research and Education (ACRE) testbed deployment was informed by the SME content analysis where a subsequent redeployment to mitigate these barriers resulted in improved performance of the IoT testbeds.

Research Questions

1. What are Lean and Green practices in the context of Indiana row crop production?
2. What are barriers to adoption of Precision Agriculture technologies among Indiana row crop producers?
3. How might a Lean and Green approach, in an Internet of things (IoT) wireless sensors framework be developed for the improved adoption of Precision Agriculture technologies among Indiana row crop producers?

1.5 Assumptions

1. The knowledge of SME's and information provided in the focused groups semi-structured interviews is assumed to be free from personal bias.
2. The semi-structured interview questionnaire contains questions developed from a structured literature review and thematic analysis and is appropriate to inform digital agriculture researchers, practitioners, precision agriculture technologists and row crop producers for adoption of Lean & Green Precision Agriculture applications.
3. The proposed research assumes inductive forms of logic for the qualitative focus groups interview methods.

4. A purposeful sampling method was used, based upon the expertise of the participants in the field of Internet of Things (IoT) for precision agriculture; focus groups were categorized based upon the assumption of that had the expertise in their respective domains related to different layers (Perception, Communication & Application) of an IoT frameworks for real time data.
5. Transitivity is the basic assumption in Interpretive Structural Modeling stating that if variable X influences Y and Y influences Z then X will influence Z transitively. This means X is related to Z through one or more variables.
6. The assumption was that the researcher participates in the action research approach and had the authority to make improvements through systematic inquiry.
7. The basic assumptions of normality, homogeneity of variance and independence of data sample is assumed for the Analysis of Variance (ANOVA) method in this study.

1.6 Limitations

1. The proposed research study is qualitative in nature and acknowledges the researcher's presence during data gathering, which was unavoidable.
2. A basic limitation, due to the nature of focus group interviews limits the study findings in their generalizability.
3. Due to budget and time constraints of this study, focus groups were limited to 3 sessions of interviews with 6 participants in each session.
4. Findings are characterized by the nature of the rigor of qualitative study. However, the statistical analysis of the coded data from NVIVO 12 software may be used to develop a grounded theory and hypotheses for the future empirical research.
5. The anonymity and confidentiality of participants may present issues when presenting findings. Steps were taken to maintain the confidentiality of the participants.
6. The basic limitations of qualitative action research methods are subject to a lack of repeatability and rigor. However empirical testing and validation of the qualitative research findings was adopted to overcome this limitation.
7. The correlation analysis performed in the study describes the relationship between two variables and doesn't imply cause and effect. Correlation analysis also cannot describe curvilinear relationships.

8. The ANOVA and regression adopted are sensitive to outliers and considers only linear relationships.

1.7 Delimitations

1. The geographical context of the research is delimited to the Indiana region of the Midwestern US.
2. The Lean and Green barriers or decision variables identified were delimited in the context of the Internet of Things (IoT) based wireless sensor framework for precision agriculture practices.
3. The participants chosen for this study were based upon expertise delimited to IoT for Precision Agriculture framework (Perception (sensors) layer, Communication layer (wireless gateway technologies), Data processing and Application layer (data storage and processing API's).
4. The sampling was delimited purposefully due to limited expertise available in the area of IoT frameworks for Precision Agriculture.
5. The nature of this research was exploratory in nature and therefore the theoretical framework proposed by this research, along with hypotheses, were less structured; this may result in an opportunity for future empirical research.
6. The statistical analysis of real time data from the IoT sensors deployed was delimited to one growing season and one-day time intervals each before and after the seasonal canopy growth.

CHAPTER 2. REVIEW OF LITERATURE

2.1 Lean and Green Models

Lean is a concept to generate a system of continuous improvement and the elimination of all forms of waste from production and supply chains to improve quality, reduce costs and add value for customers (Duarte & Cruz-Machado, 2013b; Simpson & Power, 2005). Lean management is a system that improves productivity, based upon finite resources (Hartman, B. 2015). Lean focuses on increasing output with optimized usage of input resources by reducing waste and increasing process efficiency. Green strategies focus on the elimination of environmental wastes related to water, energy, air, solid and hazardous waste (Duarte & Cruz-Machado, 2013b). Lean and Green paradigms have commonality in the context of waste reduction, continuous improvement, efficiency-driven and emphasize cleaner production (Vinodh et al., 2011; Bhattacharya et al., 2019). Verrier et al., (2016) notes the potential impact of Lean tools, such as Gemba Walk, Values Stream Mapping (VSM), Visual Management, 5S and TPM that resulted in improved environmental performance of several firms. King and Lenox (2011) demonstrate that adoption of Lean management practices in the form of ISO 9001 standards result in lower inventory levels and leads to reduction in waste generation and emissions. The benefits of implementing Total Productive Maintenance (TPM) as a Lean and Green strategy means proactive maintenance fostering environmental sustainability due to the ability of practitioners to increase machine life and mitigate potential negative effects of non-optimized functioning in the form of emissions. Chiarini (2014) underlines the impact of 5S implementation in reducing mistakes during a rubbish sorting process, leading to less repetitive strain injuries, and fostering social aspects of sustainability performance, and can foster recycling. Sustainable VSM, a term coined by Brown et al., (2014) integrates both Lean and Green concepts to track the wastes in the process and foster optimized use of resources. Pampanelli, Found & Bernardus (2014) demonstrates that continuous process improvement tools may reduce resource use from 30 % to 50% on average. For example, close supplier relationships foster information sharing on a real time basis, helpful for reducing a bullwhip effect that leads to excess production, transportation, and stock holding that ultimately impacts the environment (Leon & Calvo-Amodio, 2017). Relationships with suppliers and key stakeholders are described as an important way of ensuring strong social sustainability leading to competitive advantages (Herrera, 2015). A Lean & Greenhouse developed by Hines (2009) highlights important practices in delivery, environment, and quality pillars. The strategic house also highlights the strategic tools which support mitigation of Lean and Green waste (muda) (Hines, 2009). The positive links between human resource strategies through cultural behavior and enhancement of environmental performance is highlighted in the Lean & Green House as well (Hines, 2009).

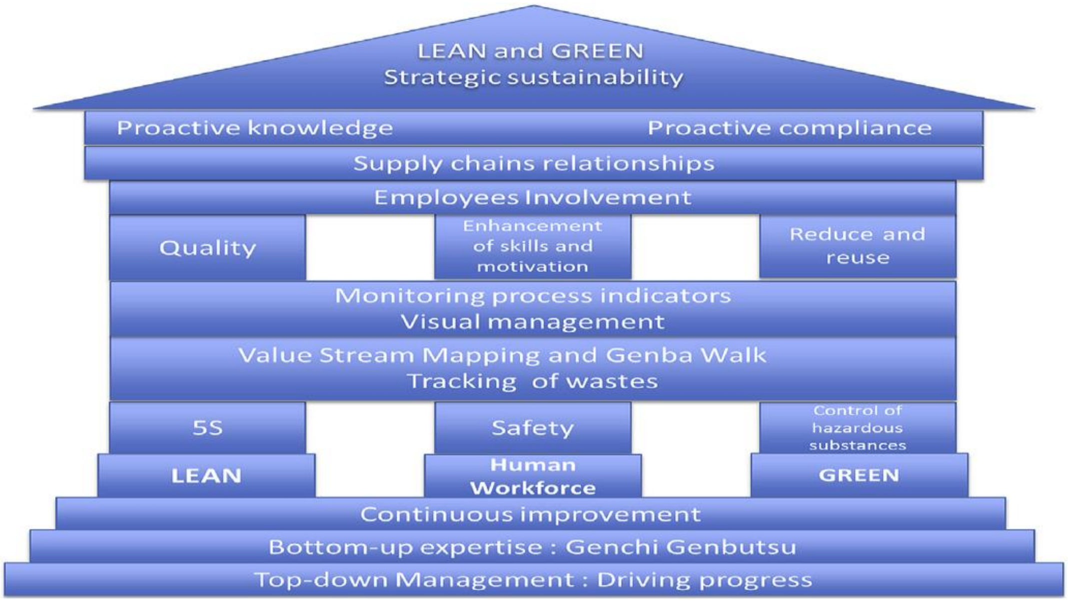


Fig. 2.1: The Lean & Green House
(Verrier et al., 2016)

Carvalho and Cruz- Machado (2009) explored the integration of Lean, Agile and Green paradigms. Synergies among these practices arise from key attributes such as capacity surplus, integration level, inventory level, production lead time and transportation time (Carvalho & Machado, 2009). Vaise et al. (2006) studied a Romanian secondary tissue paper company where the development of technical environmental projects aimed at accomplishing legal requirements and use of Lean tools such as 5S, the Kaizen philosophy and autonomous maintenance were further used to optimize the use of natural resources and production output.

The EPA published The Lean and Environmental Toolkit in December 2006 (Kidwell, 2006) to describe that conventional Lean tools may be applied to environmental waste. The manual notes using Lean manufacturing tools to improve material flow that impacts the environment such as energy, chemicals, and other kinds of waste (EPA, 2006). Biggs (2009) published an in-depth study on the integration of Lean thinking and environmental improvement, concluding that Lean thinking is capable of providing environmental benefits, though there was no direct intention to reduce environmental impact. Moreira, Alves & Sousa., (2010, July) developed a study integrating the concepts of Lean thinking and eco-efficiency and identified three main causes of production waste due to weak environmental performance: (1) Energy consumption, (2) material consumption and (3) pollutant emissions. The study also highlighted that the seven classic Lean wastes of overproduction, inventory, transportation, motion, defects, waiting and over-processing along within these environmental impact, energy use, material consumption and emissions, showed that environmental waste is embedded within these seven classic Lean production wastes. Dues et al. (2013) discussed how Lean practices act as a catalyst for greening operations and is highlighted in Figure 2.2 below.

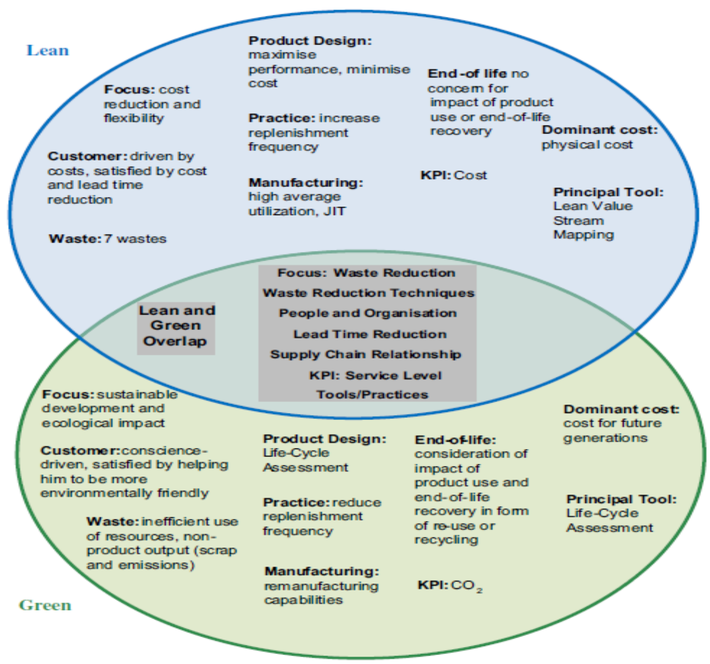


Fig. 2.2: Synergies between Lean & Green Paradigm
(Dües et al., 2013)

Lean and Green practices such as VSM, Kaizen, 5S, single minute exchange of die (SMED), standardized work, just-in-time (pull production), cellular manufacturing, total productive maintenance (TPM), Life cycle assessment (LCA), 3 R's reduction, reuse and recycling, environmental emission control and impact remediation (EEC) have been utilized to implement a Lean & Green model (Farias et al., 2019). The integration of the Lean and Green paradigm is a research topic arousing great interest but still needs further development regarding organizational methods adoption (Verrier et al., 2016). A Lean and Green matrix of Fercoq et al. (2016), integrates the seven types of Lean waste with the hierarchy of the 3Rs (reduce, reuse, recycle) of a green system, and the maturity model proposed by Verrier et al. (2016). A study by Inman & Green (2018) classified Lean and Green performance evaluation criteria based on productivity, inventory, profitability as operational performance criteria, and energy consumption as environmental performance criteria. Waste reduction, cost reduction and quality were found as criteria common to both Lean and Green paradigms. From the environmental perspective the term waste can be seen as water, raw material, energy waste or the operational side defect, scraps, overproduction etc. Waste reduction is therefore associated with cost reduction from both operational and environmental perspectives (Farias et al., 2019). The approach of total quality environmental management (TQEM) expands the narrow definition of quality by demonstrating that quality management and environmental management systems have synergistic effects (Garza-Reyes et al., 2018b).

In an action research study conducted by Pampanelli, Found & Bernardes, (2014) to develop a Lean and Green model investigated potential benefits for the environment and business processes of a manufacturing firm in terms of waste reduction, operational performance, and employee commitment. The Lean and Green Model in Figure 2.3 takes a systems approach with mass and energy flow analysis within system boundaries. The model highlights the input, operational and output metrics for Lean and Green system analysis. This is critical to understand application of Lean and Green model for systems analysis and developing key performance indicators to evaluate processes.

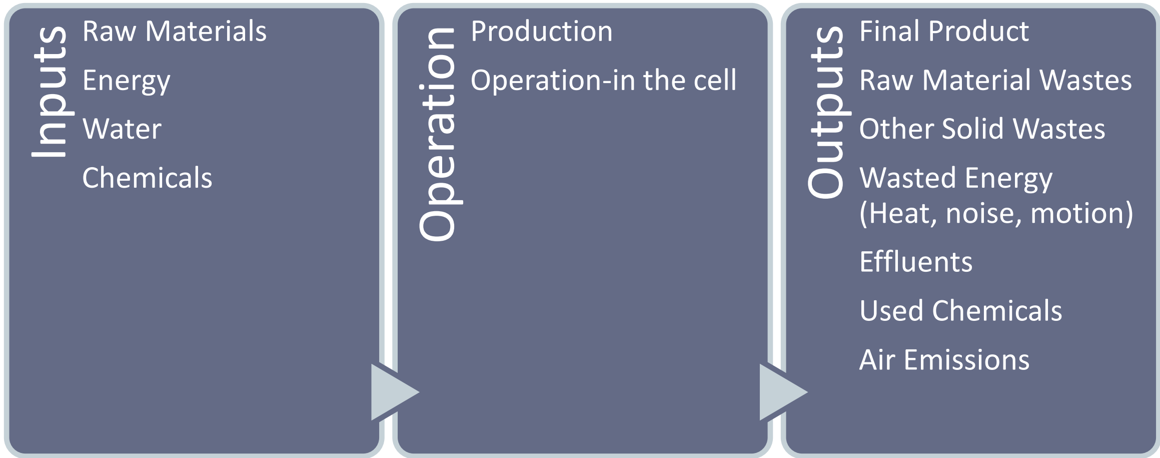


Fig. 2.3: Lean & Green Model Mass and Energy flow Analysis
(Pampanelli et al., 2014)

The Lean and Green models highlighted in this section identifies the common key concepts such as waste reduction, lead time reduction, monitoring process indicators, value stream mapping, employee satisfaction, visual management, and supply chain relationships. Manufacturing, supply chain and service operations are the most common industrial types where Lean & Green models have been adopted to assess processes (see section 2.2, table 2.1). The literature review identifies a gap related to the application of Lean and Green models to assess agriculture production processes.

2.2 Lean and Green production drivers

Growing concern of society about the environmental impacts generated from manufacturing and agricultural operations has led to changes in regulations and ecological requirements and compelled companies to pursue environmental efficiency besides operational efficiency (Garza-Reyes, 2015b; Torielli et al., 2011). Green practices emerge as a strong proponent of lean manufacturing for environmental efficiency improvement of organizations. Lean and Green strengthens the performance outcomes of organizational production systems in the context of productivity, inventory and profitability as operational performance criteria and energy consumption as environmental performance criteria (Farias et al., 2019). A study conducted by Thanki & Thakkar (2018) highlighted the Lean and Green assessment criteria factors for Supply chain performance and assessment factors respectively using Analytical Hierarchy Process methodology. The important Lean and Green production drivers, along with importance weights are highlighted in Table below.

Table 2.1: Lean & Green Assessment Criteria Weights for Supply Chain Performance (Thanki & Thakkar, 2018)

Lean & Green Production Drivers	Weight
Delivery Performance	0.594
Profitability	0.511
Operational Cost	0.489
Market Share	0.406
Employee Satisfaction	0.368
Overall Productivity	0.363
Training & Education program	0.337
Hazardous Waste Reduction	0.336
Information sharing	0.295

Delivery performance serves as the most important Lean and Green production driver as highlighted in Table 2.1, for supply chain performance. Lead time is the indicator used in the study by Thanki & Thakkar, (2018) to measure the delivery performance. Operational cost was the second most critical measure for Lean and Green assessment criteria, including costs in production, transportation and inventory holding costs. Operational cost is associated with cost of resources such as raw materials, energy, labor, and cost of waste management (Thanki & Thakkar, 2016). Lean practices help to reduce waste through elimination of non-value adding activities while Green manufacturing empathizes the efficient use of resources (Verrier et al., 2016). Therefore, Lean and Green integration helps to improve profitability, one of the second most important weighted criteria for assessment. Lean and Green practices improve labor productivity, increasing sales per employee and output per unit cost of production with the optimized use of labor and capital (Peng & Pheng, 2011). Overall productivity is an important criterion for Lean and Green assessment. The "zero defect manufacturing" mindset reduces environmental impact and ensures defect free production to increase the market share making it a criterion for assessment (Taylor, 2006). Employee training, Hazardous waste reduction and information sharing are subsequent production divers that are identified as important, connecting to positive impact on labor productivity, profitability, and delivery performance (Thanki & Thakkar, 2018).

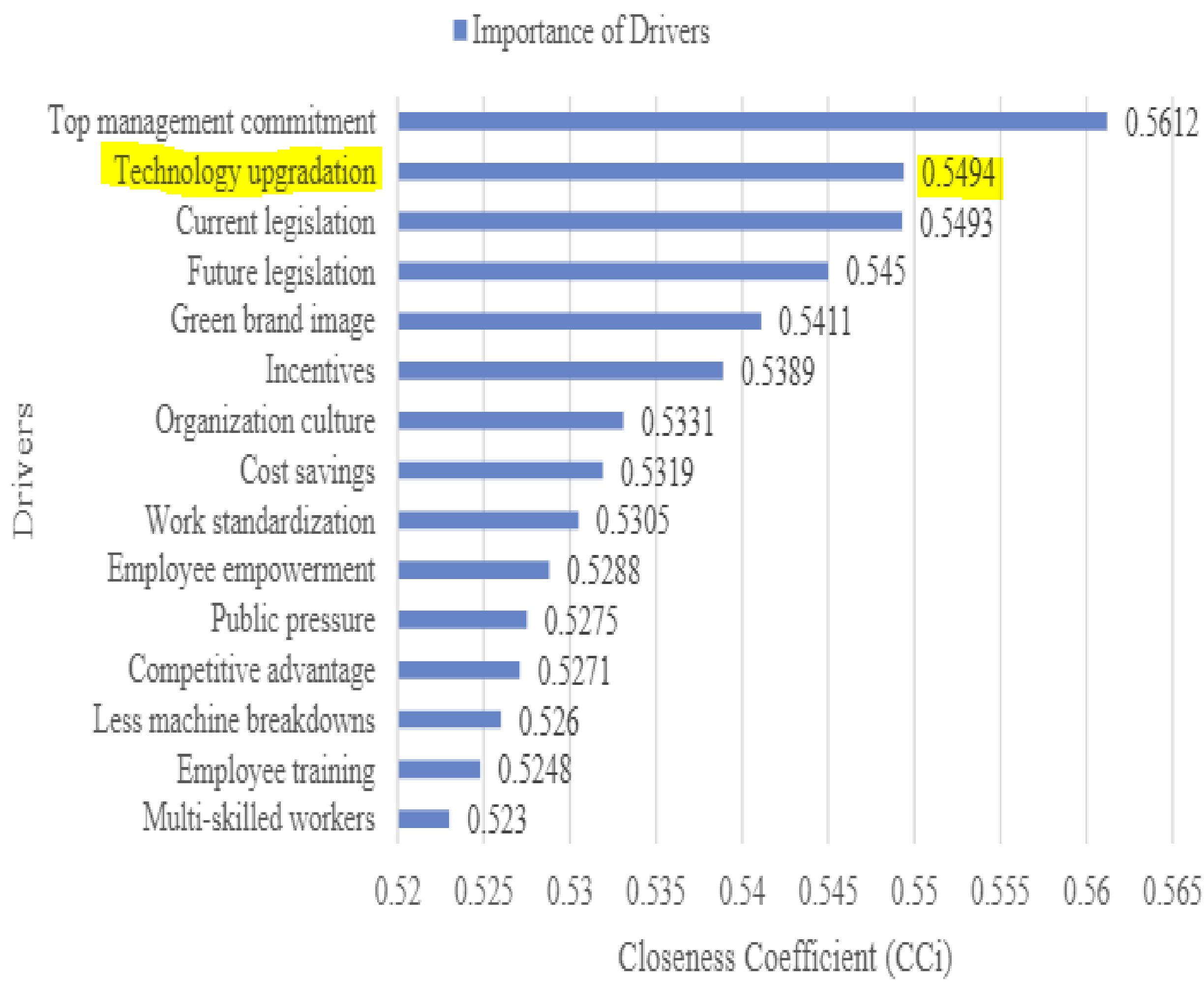


Fig. 2.4: Lean and Green Assessment Criteria Weights for SMEs
(Gandhi et al., 2018)

A study conducted by Strzelczak et al., (2017) highlighted an integrated Lean and Green model and assessed the performance of automotive supply chains. The study highlighted profitability, reliability, energy consumption, customizability, productivity, cash-turnover, value-added performance, yield, emissions reduction, lead times and inventory reduction as the drivers for Lean and Green production. Implementation of new and resource efficient technology drives the implementation process of Lean and Green practices.

Technological upgradation and adoption is a critical driver for Lean and Green system assessment as highlighted in Figure 2.4 and is utilized in this research as a metric for assessment. Manufacturing equipment or technology upgrades are listed as an important driver for Lean and Green implementation (Gandhi et al., 2018; Leong et al., 2018). Pioneering in new energy efficient technologies leads to the beneficiary results in three aspects of sustainability i.e., environmental performance (environmental), green brand image (social) and cost savings (economic) (Gandhi et al., 2018). Leong et al., (2018) highlighted a Lean and Green assessment framework consisting of five major areas such as Manpower, Machine, Material, Money, and Environment. Manufacturing equipment or technology upgrades are listed as an important driver for Lean and Green implementation (Gandhi et al., 2018; Leong et al., 2018). Assessment factors such as operational cost efficiency, less emissions, energy efficiency and waste reduction from the adoption of technology are highlighted as critical drivers Leong et al., (2018).

The impact of Lean and Green integrated strategies and practices on three sustainability pillars i.e., Economic, Environmental and Social has been explored by Bhattacharya et al., (2019) in a meta-analysis (table 2.2). The meta-analysis focuses on Economic and Environmental pillars as the scope of the research study is limited and excludes social metrics. The key drivers highlighted were operational cost, productivity, delivery performance, information sharing, employee satisfaction, profitability, hazardous waste reduction and employee training. Implementations include multiple industries, including agriculture production (Powell et al. 2017; Barth & Melin, 2018; Pearce et al. 2018; Zokaie & Simmons, 2006).

Table 2.2: Impact of Lean and Green on Environmental sustainability performance metrics (Bhattacharya et al., 2019)

Reference	Economic Metrics	Findings	Industry
Cherrafi, Elfezazi, Govindan, et al. (2017b)	Cost reduction, profitability, process improvement	The application of Lean-Green- Six Sigma integrated framework minimized the cost of energy and mass stream by 7-12%	Manufacturing Industry
Pampanelli et al. (2014)	Total costs of energy and mass	Lean and Green integration can reduce average resource use from 30 to 50 % and costs by 5-10%.	Automotive manufacturing
Azevedo et al. (2012)	Operational cost, environment cost, inventory cost	The authors proposed that the impact of Lean and Green integration on the economy is positive by reducing inventory and scrap levels.	Automotive
(Zokaei, Lovins, Wood & Hines., 2013)	Operational Cost	Lean and Sustainable production techniques report 2-3 % potential cost savings at each stage of the chain.	Read meat supply chain
Aguado et al. (2013)	Material costs, production costs, general costs, selling price	Costs and incomes can be improved with innovative environmental approaches to lean systems.	Forming tube company
Thanki et al. (2016)	Quality, cost and productivity, lead time, profitability, product design, brand value, market position, and customer satisfaction	The integration would require a combination of practices from both lean and green paradigms.	Manufacturing SMEs

Table 2.2: Continued

Reference	Environmental Metrics	Findings	Industry
Inman and Green (2018)	Reduction of air emissions, effluent waste and solid wastes and ability to decrease consumption of hazardous and toxic materials.	Indirect effect of lean practices on environmental performance through green practices is stronger, indicating complementarity.	Manufacturing
Garza-Reyes et al. (2018)	Material use, energy consumption, non-product output and pollutant releases	Implementing four lean methods (JIT, TPM, VSM and Kaizen/CI improve the environmental performance)	Mining
Helleno et al. (2017)	Electric power consumption, water consumption, harmful gases release, waste segregation	The integration of Lean and Green identified several scopes for improvement of environmental performance such as needed for implementing a measuring system.	Manufacturing
Barth & Melin, 2018	Resource efficiency, GHG emissions, Fuel consumption, Feed spillage, Labor Productivity, Employee satisfaction	Reduction in the use of diesel by 50 % improving fuel efficiency due to improvements in feed storage of silos. GHG emissions decreased due to reduction in the first calving age. Due to a more structured workplace less time was spent on searching for tools.	Agri-Farms (Dairy, Meat, Vegetables, Row-crop)
Galeazzo et al. (2014)	VOC emissions, hazardous waste	Two propositions: a) simultaneous implementation of lean and green practices were efficient more than the sequential implementation: b) collaborations between operations managers and environmental managers are important.	Manufacturing
Powell et al. 2017	Water Efficiency, Energy	Lean Six Sigma as an enabler of greater environmental sustainability in dairy processing industry.	Dairy Industry

2.3 Lean and Green practices in agriculture

Environmental sustainability assessments have traditionally focused on agriculture (Scherr & McNeely, 2007). Researchers and policy makers have tried to develop more holistic approaches by incorporating stages of food processing, transportation, and food retailing in assessment frameworks of food supply chains (Heller & Keoleian, 2003). A number of authors have investigated various aspects of Lean and Green in food production (Barth & Melin, 2018). Prior studies utilized Lean and Green techniques in food production to assess economic costing (Pretty et al., 2005), lifecycle approach to sustainability impacts energy accounting in product lifecycle (Carlsson et al., 2003), mass balance of food sectors, ecological footprint (Ridoutt et al., 2010), and farm sustainability indicators (Rodriguez et al., 2010). A case study conducted in Swedish Farms revealed the potential for synergies between Lean and Green initiatives (Barth & Melin, 2018). If synergies are supported, the agricultural sector may be more receptive to change programs when shown how Lean and Green may be combined to promote sustainable economic profit and environmental benefits. A most valuable tool in the combination of Green and Lean is the Value Stream Mapping tool that can be used to quantify the carbon footprint of the food production processes (Johnsson & Weidman, 2016). Mapping of carbon emissions in various sub-processes can help farmers work more strategically to reduce their farms' negative environmental effects (Barth & Melin, 2018). A case study conducted in the Columbian coffee sector where Lean and Green assessment of six coffee producing farms highlighted the evaluation factors such as value stream mapping (VSM), Just in Time (JIT), Life Cycle Analysis (LCA), Reusing, Reducing, Recycling (3R’s), Gemba Walk and employee training (Reis et al., 2018). A case study conducted by Powel et al., (2017) in the Norwegian dairy industry focused on reducing raw material usage in milk production, thus improving resource efficiency impacting environmental sustainability and increasing milk yield at the same time by implementing Value Stream Mapping (VSM). A case study conducted in Horticulture Agri-production of apples and pears (Pearce et al., 2018) highlights the operational integration as being an imperative strategic contributor to Lean and Green. A study conducted by (Wiese et al., 2015; Yang & Suh., 2015) highlighted the operational practices directed at driving sustainable performance as a direct determinant of the key process indicators in the agri-food supply chain. Therefore, most of the studies conducted in the area of Lean and Green practices in agriculture focuses on the operational context with Value Stream Mapping, employee training, Gemba Walk, Life cycle analysis, Reducing and Recycling as common tools used to streamline processes. However, there is a gap identified through literature review analysis regarding no application of Lean and Green practices in technological context. This thesis explores the Lean and Green technological practices through Precision Agriculture to foster economic and environmental sustainability. The following section highlights the Lean and Green issues in Midwest region row crop production.

2.4 Midwest region row crop sustainability issues

The production of row crops in the Midwestern region of the US has been facing environmental and economic sustainability issues. The key challenges affecting row crop production are overcoming barriers to adoption of energy-conserving production practices and improving the viability of bioenergy production (Karlen et al., 2012). Energy costs represent more than 22% total costs for soybean production in 2004 (Shoemaker, McGranahan & McBride, 2006). Average irrigation water use in soybean production has increased by around 50% from 180 m^3/ha in 2002 to 270 m^3/ha in 2012. The "ethanol decade" has demanded expansion of cropland under soybean and the area under irrigation. Freshwater ecotoxicity impact per ha soybean production increased by 3-fold from 2002 to 2012 (Yang & Suh, 2015). Nitrogen fertilizer represents a significant energy and cost input for soybean production. Several methods for decreasing N fertilizer use per unit output have been identified, including the use of crop rotations, cover crops and manure (Karlen et al., 2012).

The trends pertaining to the application of Nitrogen and Phosphorous are shown in the Figure 2.5 and Figure 2.6 below, highlighting that there is an increasing trend over the past 20 years 1990-2019, for Indiana, the scope of this study (USDA NASS Indiana, 2019). Optimizing the input application of Nitrogen and Phosphorous could reduce freshwater in toxicity and reduce operational costs.

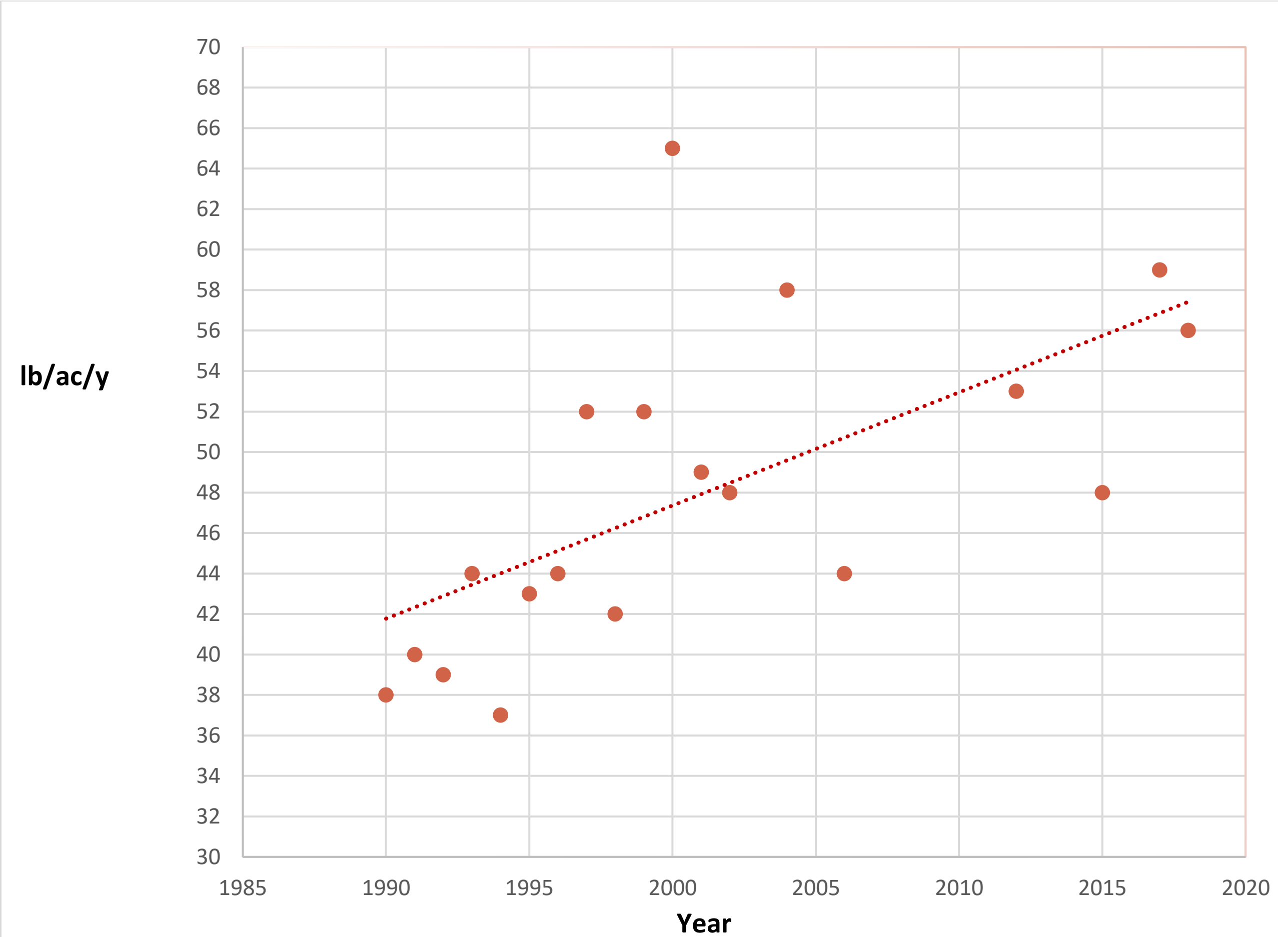


Fig. 2.5: Phosphorous application rates for- soybean production in Indiana (1990-2019) (USDA NASS Indiana database)

The increase in Phosphorous & Nitrogen application was 35 % and 20 % for past 30 years in Indiana row crop production. The increases in corn & soybean yields for past 30 years were 39 % and 38 % in Indiana row crop production (USDA NASS Indiana, 2019). However, the proportional increase in yield was 3 % and 19 % for Phosphorous & Nitrogen application on soybean & corn respectively. Therefore, there is significant scope for optimization of fertilizer inputs to further improve the proportional increase in yields.

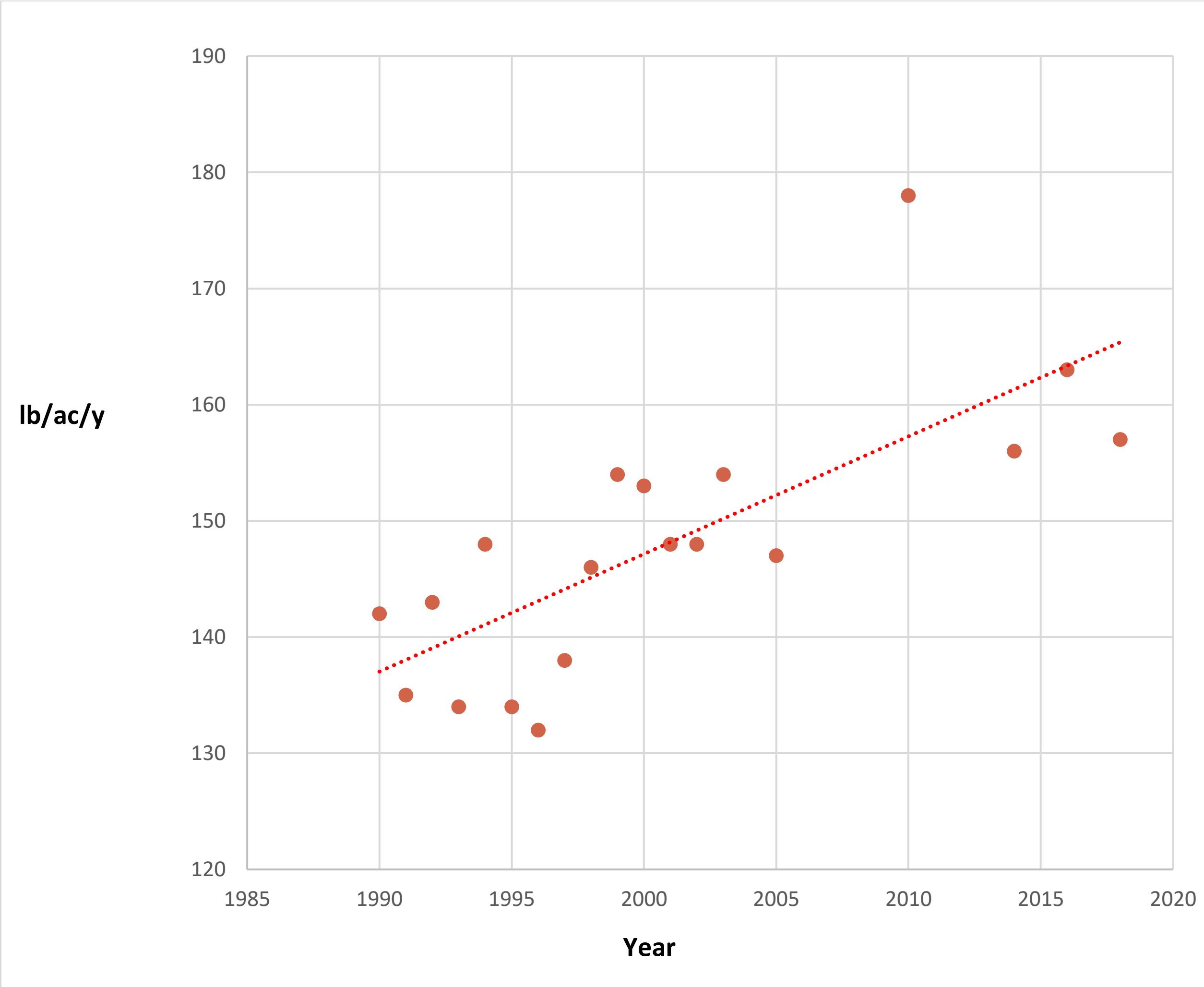


Fig. 2.6: Nitrogen application rates for- soybean production in Indiana (1990-2019) (USDA NASS Indiana database)

From the economic perspective the total operational cost of soybean production in Indiana has seen an increasing trend (2003-2018) (USDA NASS, 2019). The data for total operational cost highlighted by metric $/Operation means total operational cost per all the farm machinery operations performed (seeding, harvesting) for total soybean production in Indiana state. The metric $/farm for fuel cost means total cost of fuel consumption per all the farm machinery operations performed (seeding, harvesting) for total soybean production in Indiana state.

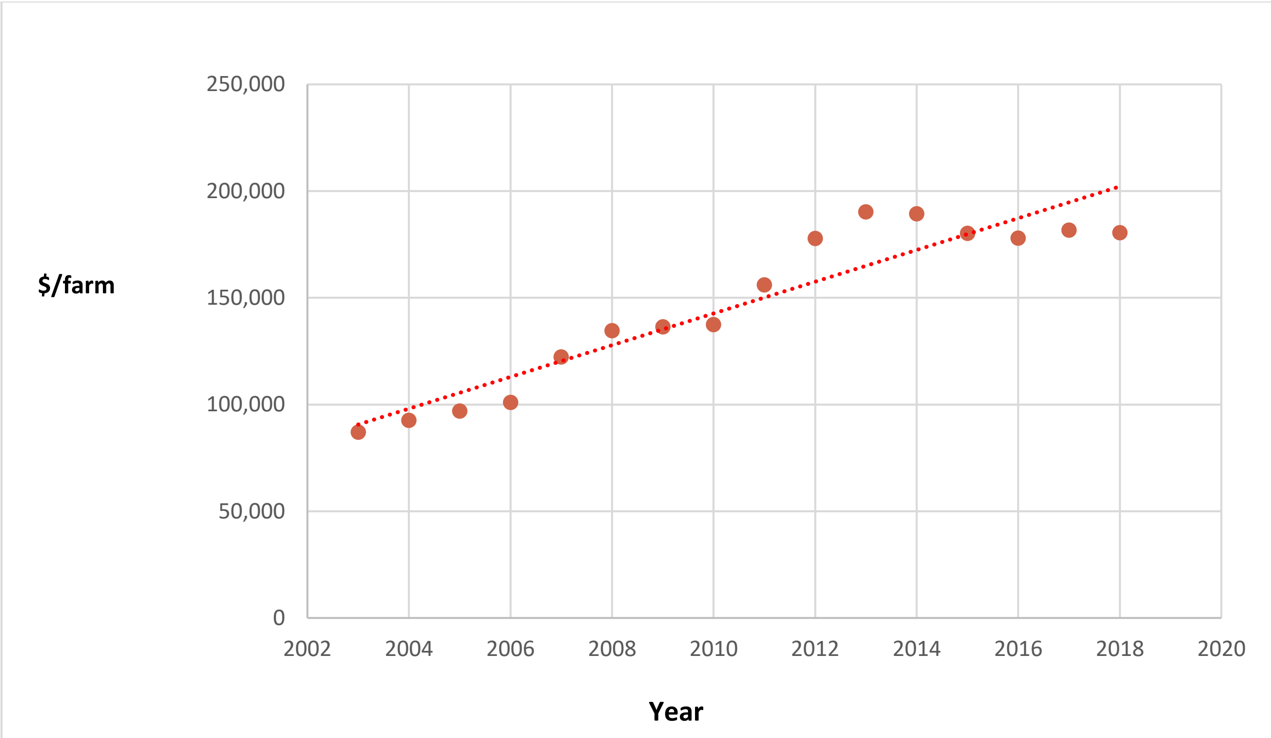


Fig. 2.7: Total Operational Cost- soybean production Indiana (2003-2019)
(USDA NASS Indiana database)

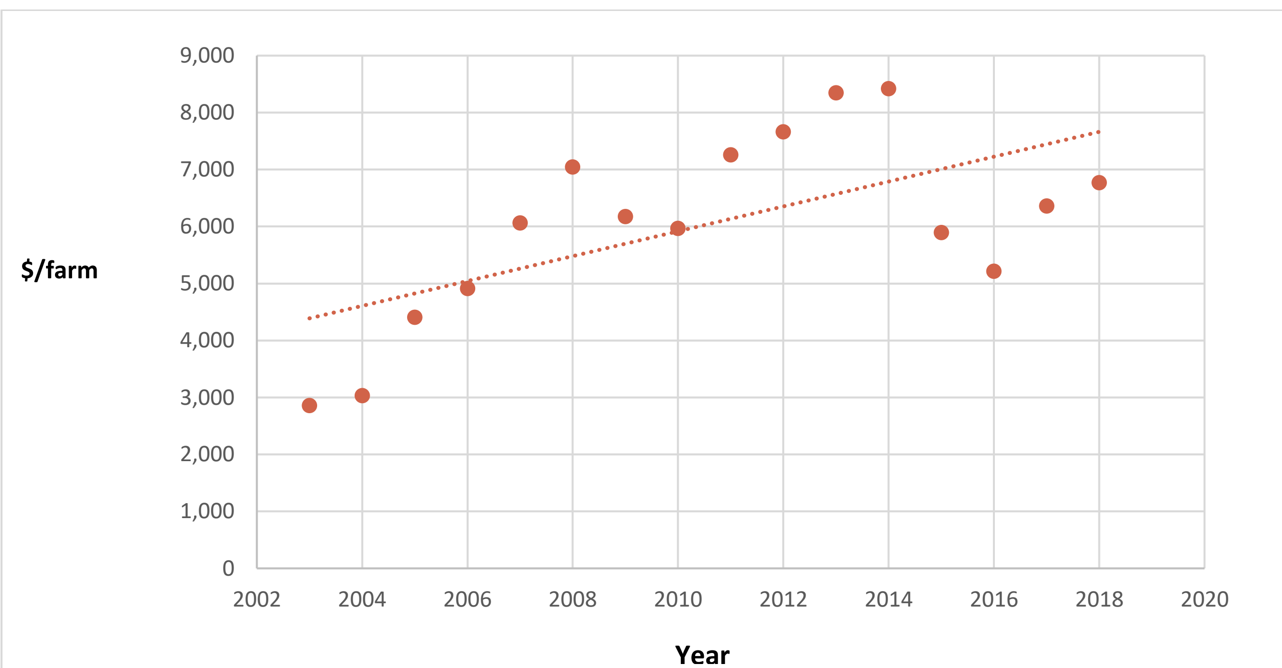


Fig. 2.8: Fuel Cost- soybean production Indiana (2003-2019)
(USDA NASS Indiana database)

The labor productivity in economic metric $/hr for soybean production has decreased slightly from 2008 to 2019.

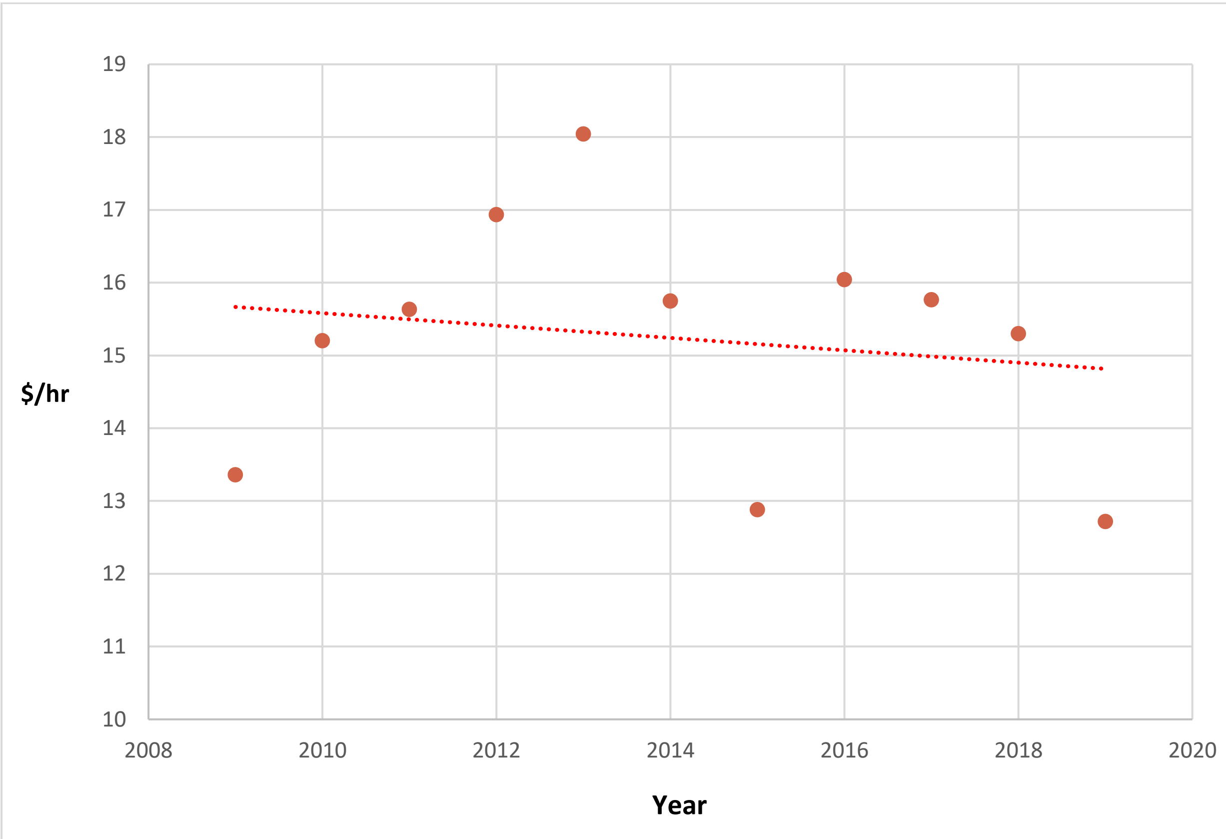


Fig. 2.9: Labor Productivity- soybean row crop production Indiana (2009-2019)
(USDA NASS Indiana database)

The rate of increase in operational costs and decrease in labor productivity highlights that there is decreasing trend in economic sustainability performance metrics of labor productivity, increased operational cost), and decrease in environment sustainability performance metrics increased fertilizer application, nitrogen & phosphate application, increased fuel consumption (USDA NASS Indiana, 2019). A response improving agriculture production has been through adoption of Lean and Green principles, expressed through technology deployment and adoption.

2.5 Precision Agriculture

Precision Agriculture practices relates to Lean and Green production through a focus on improving outcomes, defined by agriculture drivers. Precision agriculture technologies foster optimized application of agriculture inputs, including seeds, fertilizers, water, pesticides, and energy that result in savings on the input applications, resulting in increased yield, and improved profitability. Precision Agriculture technologies potentially provide producers improved tools to manage inputs and optimize factors of production such as fertilizer, pesticides, and seed application. The definition of precision agriculture published by the National Research Council (1997) defines precision agriculture as “a management strategy that uses information technology to bring data from multiple sources to bear on decisions associated with crop production”. Precision agriculture tools include information gathering tools such as yield monitors, targeted soil sampling and remote sensing tools; variable rate technology; guidance systems such as light bars and auto steer equipment. Precision Agriculture Technologies include soil mapping, variable rate application, yield monitoring mapping, automatic steer global position guidance systems and autonomous vehicles (Say, Keskin, Sehri & Sekerli, 2018). Management zones in the field are developed by using crop and field information. Varying input rates increase yields or reduce costs depending on the managers’ goal for the management zones (Adrian et al., 2005).

The potential benefits of Precision Agriculture technologies are similar to benefits from Lean and Green practices. These include an increase in the accurate placement of inputs, reduction of machinery costs from an increase in machinery field capacity and reducing GHG emissions due to reductions in input usage for a given level of production (Griffin 2009; Shockley 2010). Precision Agriculture technologies have an impact on increasing profitability, reduction in operational cost, increasing labor productivity, reduction in cycle times of operation, optimizing fertilizer (nitrogen & phosphate application) and decreasing fuel consumption in farm machinery. These technologies may consist of variable rate application (water & fertilizer), real time kinematic (RTK) autosteer, guidance systems (GPS guided autosteers, yield monitors), submeter accuracy auto steering (SUB) and telematics. In a study by Brown et al. (2016), the authors note the impact of Precision Agriculture technologies, such as auto-steer guidance, automatic section control spray application and Real time kinematic precision tractor operations, on the carbon emission and economic operational cost in the corn and soybean production in the US state of Kentucky. The findings indicate that automatic section control spray application has the capability to spray more precisely, reducing the over-application of inputs and having a mean net return of 0.47 % (Brown et al., 2015). Real time kinematic precision tractor operations provided the most significant improvement in carbon footprint ratio of 2.74 % with increased technical efficiency in applying nitrogen and seeds more accurately (Brown et al., 2015). Labor productivity also increased allowing more desirable production practices to be employed (Brown et al., 2015). Global navigation satellite systems-based auto steering reduces overlap between tractor passes and overall operator fatigue increasing productivity (Holt et al., 2013). A study conducted by (Van Evert et al., 2017) to assess the impact of implementation of Precision Agriculture Technologies in Potato and Olive production highlighted that Variable Rate Application (VRT) of Potassium and Phosphorus fertilizers, leading to a strong reduction in nutrient use and increase in operational profits of 21%, with increase in profits by 26%. Precision Agriculture can help in managing crop production inputs in an environmentally friendly way by utilizing site specific knowledge targeting rates of fertilizers, seed and chemicals improving soil conditions (Bongiovanni and Lowenberg-DeBoer, 2004).

Research Question 1 (R1): What are Lean and Green practices in the context of Indiana row crop production?

Lean and Green production drivers, through Precision Agriculture practices are described in Table 2.3 through structured literature review using NVIVO 12 coding for thematic content meta-analysis of 65 peer reviewed journal articles described below in Chapter 3 Methodology section 3.2.

The Lean-Green production drivers specifically Profitability, Operational Cost, Data Sharing and Hazardous waste reduction were used in this study to understand the barriers for adoption of IoT based Precision Agriculture practices (variable rate irrigation, variable rate fertilization, cloud-based analytics, and telematics for farm-machinery navigation among Indiana row crop producers). The technical, operational, data management and cost barriers related to adoption of IoT wireless sensors framework for Precision Agriculture practices were studied through Lean-Green drivers.

Table 2.3: Results of Meta-Analysis of Precision Agriculture Technologies of R1.

Lean and Green production drivers	Precision Agriculture Technologies Impact	Crop type	References
Delivery Performance	● Real time kinematic precision tractor operations reduced the turnaround time of tractor operations thereby decreasing the carbon footprint ratio of 2.74 %. ● The global navigation satellite system-based auto steering reduces overlap between tractor passes thereby decreasing turnaround time. ● Controlled Traffic Farming (CTF) is a precision agriculture technology reducing machinery loads to the least possible area of permanent traffic lanes and optimizing driving patterns for more efficient operations (i.e., reduced overlaps) and targeted input applications.	Corn, Soybean, Potato, Olive	Brown et al. 2015, Holt et al. 2013, Balafoutis et al, 2017
Profitability	● Variable Rate Technology was profitable than uniform rate with a profit margin of $37.14 per hectare in corn and soybean production. ● Variable rate application (VRT) of Potassium and Phosphorus fertilizers in potato production led to a strong reduction in nutrient use and increase in operational profits by 21 % with increase in social profits by 26%. ● The submeter accuracy auto steering precision agriculture technology provided 0.42 % in mean net returns over the base in corn and soybean production in the Kentucky region. ● Grid sampling-variable rate fertilization generated a net return of $48 more per acre than the conventional fertility management strategy in sugar-beet production.	Corn and Soybean, Potatoes, Sugarbeet.	Wang et al, 2003, Van Evert et al, 2017, Brown et al, 2015.

Table 2.3: Continued

Operational Cost	• The total operating cost was .08/kg of maize production under precision agriculture system as compared to .09/Kg under convention system depicted by a case study in Brazilian farms. • Variable rate application (VRT) technology in corn production led to $25/acre savings in operational cost. • Precision agriculture technologies such as yield mapping led to 4.5%, GPS soil mapping 2.4 %, guidance systems 2.7 % and VRT 3.9 % in operational cost savings.	Maize, Soybean,Corn	Silva et al, 2007, Schimmelpfennig, D. (2016)
Employee Satisfaction	• Precision agriculture technologies have high adoption rates in the US with yield mapping used on about 40 % of US corn farms and soybean acres, GPS soil maps on about 30%, guidance on over 50% and VRT on 28-34 percent of acres. • Farmers surveyed in England reported that PA technologies were used mostly for improving information accuracy 76 %, reducing input costs 63 %, improving soil conditions 48 %, improving operator conditions 36% and reducing greenhouse gas emissions 17 %. • Yield monitors a precision agriculture technology is used with 4500 combines in the US to harvest about 46 % of corn, 36 % of Soybean and 15 % wheat with yield monitors	Corn, Soybean	Schimmelpfennig, D, 2016, Say et al, 2018, Fountas et al, 2005
Overall Productivity	• Guidance systems such as light bars and auto steering can reduce working hours of operators in the field by 6.04 % and improve fuel efficiency by 6.32 % increasing labor and farm machine productivity • Adopting GPS-guided or auto-steered combines and tractors can reduce operator errors by determining precise field locations (that are often difficult to determine accurately by sight) and compensating for operator fatigue thus increasing overall labor productivity. • Real time kinematic autosteer technology reduces overlap and number of passes required over the field for input application increasing fuel efficiency by decreasing fuel consumption by 10.43 %.	Corn, Soybean	Bora et al, 2012, Griffin et al, 2004, Brown et al, 2015, Shockley et al, 2011

Table 2.3: Continued

Information Sharing	• Site specific management precision agriculture technology use information technology to monitor and control data collection for temporal and special allocation of inputs • Field operators using guidance systems have timely, accurate information about coordinates accessible from a screen in the cab. • Guidance systems save money by reducing over- and under-application of sprays and better aligning the seeding of field crop row. • Precision Agriculture encourages site specific crop management defined as the management of spatial and temporal variability at a sub field level to improve economic returns and reduce environmental impact.	Wheat, Corn, Soybean	Lowenberg-Deboer and Swinton. 1997, Koch et al. 2004, Blackmore et al, 2003.
Hazardous Waste Reduction	• Variable rate application technology reduced N by 36 % while increasing yield. • Variable rate nitrogen application technology reduced $N0_3N$ by 50 % decreasing N application from 60 to 29 kg/ha. • VRT resulted in reduction of herbicide use by 42 % in corn production.	Wheat, Barley, Corn, Soybean	Griepentrog and Kyhn, 2000, Larson et al, 1997, Brown et al, 2015

2.6 Internet of Things (IoT) wireless sensors framework for Precision Agriculture

Internet of Things (IoT) wireless sensors communication networks have fostered Lean and Green farming applications shown in Table 2.3. Farm data shared by devices fosters data-based decision making among producers, boosting productivity, and minimizing waste encouraging optimal use of resources. The Internet of Things (IoT's) applications in agriculture, with sensors, have been demonstrated in a study to improve crop yields or quality and to reduce costs (Ojha et al., 2015; Talavera et al., 2017). An evaluation of micro-climatic weather conditions for embracing the production uncertainties and maximizing the returns and emission free closed- field crop cultivation is highlighted in the study (Redmond et al., 2020).The application of IoT sensors used for web-based decision support systems communicating with a WSN for irrigation scheduling in olive fields using data from humidity, solar radiation, temperature and rain gauging sensors is highlighted in the study (Diedrichs et al., 2014). Internet of Things (IoT) for agriculture sensors and precision agriculture applications are classified into five categories (1) climate, (2) livestock, (3) plant, (4) soil, and (5) water. The fig below highlights the different types of IoT wireless sensors for developing Precision Agriculture applications based on climate, livestock, plant and soil monitoring.

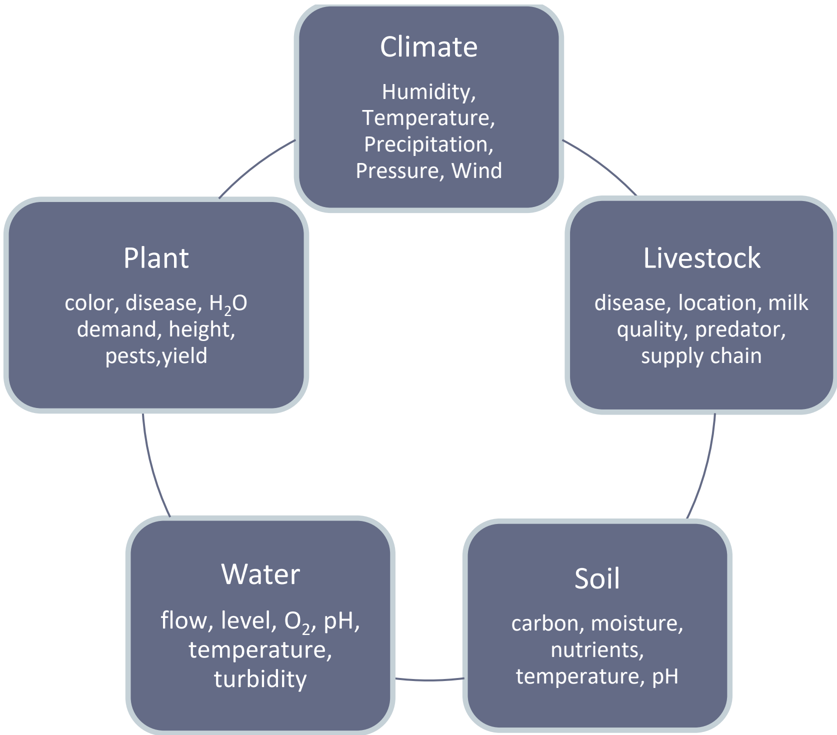


Fig. 2.10: Critical measurable production variables in Precision Agriculture applications that could be captured by sensors
(Antony et al. 2020)

Different types of sensors (temperature, humidity, light, pressure, wind speed) receive and collect data managed by cloud information management systems for data analysis solutions through application programming interfaces (API's) (Navarro, Costa & Pereira, 2020). A study conducted by Hashim, Mazlan, Aziz, Salleh & Mohamad, (2015) reviewed the control with an electronic device (arduino) of temperature, soil moisture and used Android- based API's for functionality. Hashim et al., (2015) also highlighted notes the advantages of low cost and flexibility for agriculture control in contrast to expensive components such as high-end personal computers A study conducted by Pahuja et al., (2018) highlighted an online microclimate monitoring and control system for greenhouses. The system was supported by a WSN for gathering and analyzing plant sensor data to provide control of climate, fertilization, and irrigation. Luan, Fang, Ye & Liu, (2015) developed an artificial system that integrated drought monitoring and forecasting irrigation into a platform based on IoT's hybrid programming and parallel computing. Muangprathub et al., (2019) focused on leaf spot disease assessing the crop-weather-environment-disease relations. The different types of IoT sensors for agricultural applications in the table below.

Table 2.4: Type of Sensors and lean & green application in agricultural processes
(Patil, Al-Gaadi, Biradar & Rangaswamy. 2012)

Type of Sensors	Agriculture Applications	Lean & Green Precision Agriculture Applications
Optical	Crop height measurement, N content, solar irradiance, plant disease, crop waste	Pest control & Early disease detection system
Thermistor, Thermocouple	Soil temperature, water temperature, seed and crop storage temperature	Precision Irrigation, Crop monitoring
Pressure and flow rate	Irrigation water flow	Precision Agriculture
Acoustic	Animal detection, water level, grain silo level	Livestock monitoring
Accelerometer	Livestock monitoring, crop transport.	Livestock monitoring
Electrochemical	$C0_2$ greenhouse concentration, beehive monitoring	Precision Fertilization
Electrical Conductivity	Soil moisture, soil and water PH, ambient humidity	Soil Health, Precision Irrigation
Electrical Capacitance	Soil moisture, ambient humidity	Crop monitoring
RFID	Livestock and poultry tracking, supply chain tracking, asset tracking.	Livestock tracking, supply chain tracking.
GPS (location)	e-Extension, equipment navigation, livestock tracking, asset tracking.	Farm machinery navigation and Livestock tracking.

A wireless sensor IoT framework highlighted in the Figure below consists of Perception layer, Communication Layer, Data processing & Application layer.

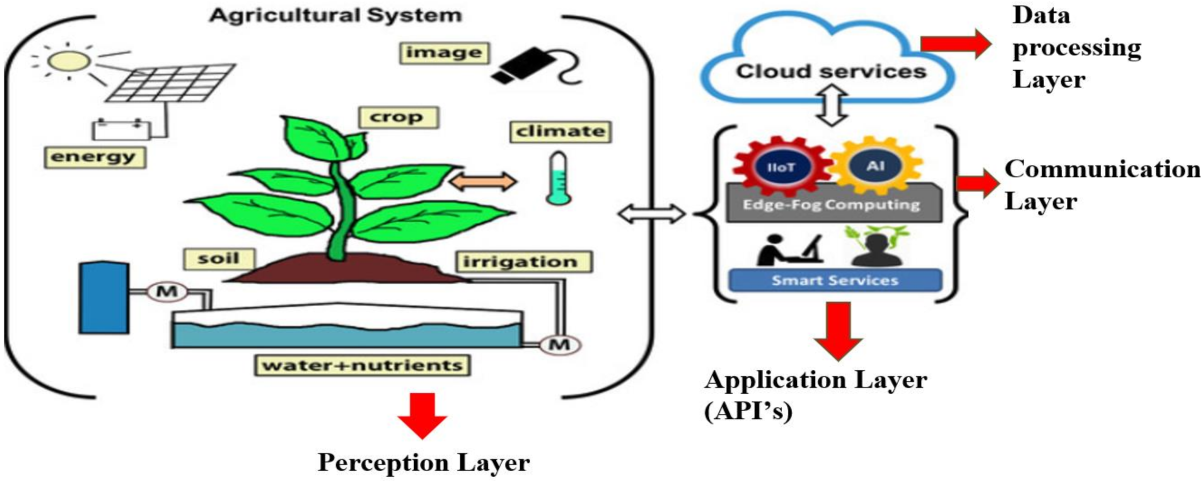


Fig. 2.11: An Internet of Things (IoT) wireless sensors framework for Precision Agriculture applications
(Ferrández-Pastor, García-Chamizo, Nieto-Hidalgo & Mora-Martínez. 2018)

The combination of different types of sensors may be used as a perception layer in IoT framework noted above in Figure 2.10 to gather data related to environmental, crop and soil factors. The combination and type of sensors used depends on factors to develop Precision Agriculture applications. Multiple studies highlight the application of different types of IoT sensors in Lean and Green precision agriculture applications. Multiple studies demonstrate that IoT decision support systems, utilize data from different types of sensors to inform growers when to apply inputs, resulting in effective disease mitigation, improving yields, and saving 500 USD reducing operational cost (Feng et al. 2017; Van Evert et al. 2017). Internet of Things decision support systems may also be used to integrate weather data and electrical capacitance sensors for real-time monitoring of soil water content along with soil water balance to develop irrigation scheduling models. Developed irrigation scheduling models to provided recommendations to wheat farmers on timing and intensity of irrigation, resulting in water savings of at least 25% compared to traditional scheduling (Saab, Sellami, Giorio, Basile, Bonfante, Rouphael & Albrizio, 2019).

The data from the perception layer transfers through wireless communication networks and protocols (Zigbee, BLE, Wifi, GPRS, LoRa, Sigfox). The constraints of communication range, power availability, data transfer rate, data storage, cost and scalability determine the type of protocol to use for a particular type of precision agriculture application. The data from the wireless communication gateway technologies is transferred to a data processing layer that can be a cloud or Application programming interface (API) depending upon the type of precision agriculture application at the user-end interface. The data gets processed in the cloud and different API's may be developed, depending upon the Precision Agriculture applications. The IoT wireless sensors-based Precision Agriculture barriers described below are crucial to understanding Lean and Green adoption.

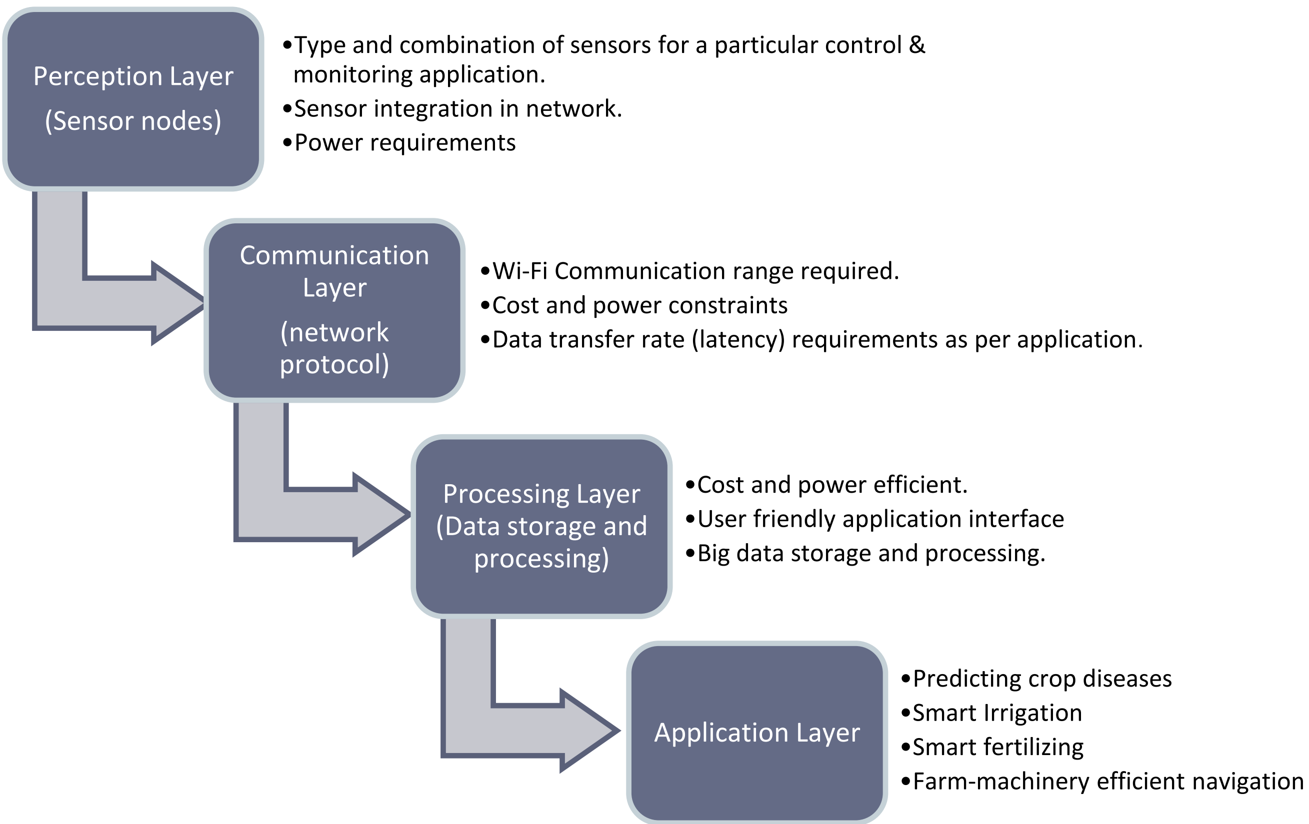


Fig. 2.12: The issues for adoption of IoT wireless sensors-based Precision Agriculture practices among Midwestern producers (Navarro, Costa & Pereira. 2020, Jawad et al. 2017)

2.7 Barriers to Adoption of IoT Precision Agriculture Technologies among Producers

The adoption of precision agriculture technologies among row crop producers in the US Midwest region has been increasing (Erickson & DeBoer, 2019). Erickson & DeBoer, (2019) note the adoption of different precision agriculture technologies among Mid-west region producers. Yield monitoring technology has the highest adoption rates at 69% of farmers reported adopting it. Variable rate fertilizer (39%), variable rate pesticide (8%), variable rate irrigation (4%), cloud-based data analytics (21%) and telematics (10 %) are all reported lower adoption rates. Some of the challenges for adoption of IoT based Precision Agriculture include cost-effectiveness, internet availability near farms, power availability, data scalability and interoperability (Erickson & DeBoer, 2019). Multiple studies note Socio-economic factors (farmers educational level, age), Agro- ecological factors (soil quality, farm size, ownership of land), Farmer's perception (perceived benefits vs profitability), Technological factors (computer education, data aggregation) and Informational factors (extension services) as factors having a positive relationship with adoption (Tey & Brindal. 2012; Castle, Lubben & Luck. 2016). Technical, operational and management issues highlighted in the Figure 2.13, are also validated by Jawad et al., (2017). The factors include enumerating cost, power consumption, communication range, data latency, data scalability, data storage and data interoperability (Jawad et al., 2017). A more recent study conducted by USDA NRCS., (2020) highlighted cost of equipment, less benefit, training, data scalability, communication range and time of implementation as the IoT Precision Agriculture barriers.

In summary, the structured literature review (SLR) utilized in this study explored and identified the Lean and Green drivers, in context of Precision Agriculture practices specifically, IoT based. Internet of Things wireless sensors-based Precision Agriculture applications of monitoring row crop diseases, smart irrigation, smart fertilizing, cloud-based analytics, and telematics for farm-machinery navigation have a low rate of adoption among Indiana row crop producers. These barriers include technical (power limitations, communication range), operational (data scalability, sensor distribution, data latency), management (data storage, data interoperability & data processing) and finance (cost, return on investment).

Next, the focused group interviews, Interpretive Structural Modeling and Action research methods are discussed to answer the research questions of this study in the following Chapter.

CHAPTER 3. METHODOLOGY

This chapter covers the research framework, data collection methods and data analysis methodologies applied in this thesis.

3.1 Research Framework

The objective of this research was to explore Lean and Green Internet of things (IoT) wireless sensors framework for the adoption of Precision Agriculture applications (monitoring row crop diseases, smart irrigation, smart fertilizing, and farm-machinery efficient navigation) among row crop producers in the Indiana region. The research questions, research methodology, data collection and data analysis methods applied are described in the table below.

Table 3.1: Research Framework

Research Questions	Research Methodology	Data Collection	Data Analysis
What are Lean and Green practices in the context of Indiana row crop production?	Structured Literature Review	Search Engines- Google Scholar, Purdue Libraries, IEEE, Emerald, Elsevier and ScienceDirect targeting peer reviewed journal articles. USDA NASS Indiana Database	Thematic content analysis
What are barriers to adoption of Precision Agriculture technologies among Indiana row crop producers?	Structured Literature Review Focused group semi-structured Interviews	Search Engines- Google Scholar, Purdue Libraries, IEEE, Emerald, Elsevier and ScienceDirect targeting peer reviewed journal articles.	Thematic content analysis

Table 3.1: Continued

How might a Lean and Green Internet of things (IoT) wireless sensors framework be developed for the improved adoption of Precision Agriculture technologies among Indiana row crop producers?	Focused group semi-structured Interviews Interpretive Structural Modeling (ISM) Action research deployments comparison Correlation analysis	Focused groups semi-structured interviews.	Coding of Interviews followed by content analysis using Interpretive Structural modeling.
Does Battery Power Consumption of IoT sensor nodes deployed vary significantly with Communication Range (CR), Data Rate (DR), Received Signal Strength Index (RSSI) and Signal to Noise Ratio (SNR)?	Multiple linear regression	Real time data points (n=2505) from Ag Sensors deployed at Purdue test beds.	Analysis of Variance for Multiple linear regression.

3.2 Structured Literature Review & Thematic analysis

The research methodology framework followed a structured literature review and thematic analysis of a focus group, subject matter expert semi-structured interviews, and data analysis through a content analysis approach. The basic definition of content analysis as stated by (Berelson, 1952) is "content analysis is a research technique for the objective, systematic and quantitative description of the manifest content of communication". The four-step process model of content analysis by Mayring. (2008) and Downe- Wamboldt. (1992) is delimits the material to be analyzed by defining a unit of analysis, creating analytical categories, defining the material collection (creating and defining categories), pretesting the categories defined, refining through pretesting and refining categories and analyzing the data by coding for thematic analysis through coding and analyzing data. The first step was selecting the unit of analysis i.e., the peer reviewed journals and data reports covering the period from 1990-2019 (USDA NASS, 2019). The peer reviewed literature was selected from top-tier publishers Elsevier, Emerald, IEEE, Taylor Francis, Inderscience and Science direct. The second step was defining categories with inclusion and exclusion criteria. Category schemes were created by the researcher based on the research questions, the selected unit of analysis, relevant theories, and a review of the initially selected sample journal articles and data reports. The third step was pretesting and refining categories in which an initial sample was carefully analyzed for progressive refining and validating of the category scheme. The fourth and the last step was coding and analyzing the themes, per defined categories. A coding system is more reliable if the critical attributes of specific categories are defined and in high agreement with the category definitions. The content themes identified for this for this study were based on Lean and Green drivers, Precision Agriculture practices and barriers to adoption of IoT based Precision Agriculture practices and used to develop semi-structured focused group interview questions. These questions were used to understand barriers and define related decision variables for a participatory action research approach.

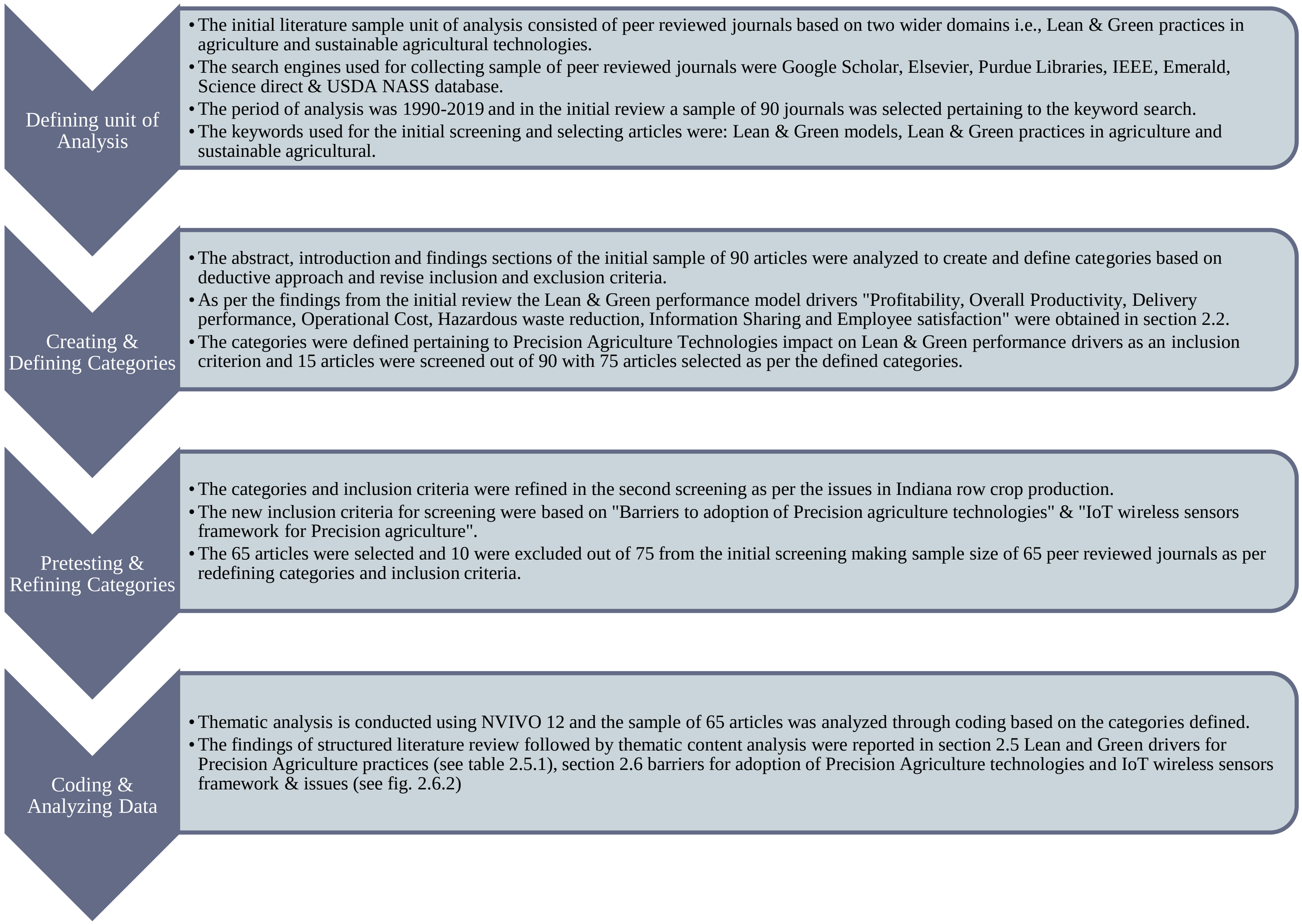


Fig. 3.1: Content Analysis approach for the Structured Literature Review

3.3 Data Collection Methods

This section includes the data collection methods applied in the thesis, specifically focused group semi-structured interviews, Participatory Action Research deployments of sensors and creation of a real time data pipeline.

3.3.1 Focused group semi-structured interviews

Figure 3.2 highlights the methodology approach followed for this study consisting of structured literature review, focused group semi-structured interviews, informed action research deployments and comparison of IoT sensors deployments based on improved Lean and Green design. The data collection methods include focused group semi-structured interviews followed by validation of findings, with triangulation from the SLR and action research finding of IoT sensors deployments at the Purdue Agronomy Center for Research Education (ACRE) research farm site. Denzin & Lincoln, (2008) defined the term "focus group" to apply to a situation in which the interviewer asks group members very specific questions about a topic after considerable research. Focus groups are used in the studies to investigate complex systems where the research can interact with participants and there is further opportunity to ask for clarification questions. Krueger (1988, p.18) defines a focus group as a "carefully planned discussion designed to obtain perceptions in a defined area of interest in a permissive, non-threatening environment". The critical element of focus group interviews is the involvement of people where the information encourages a nurturing environment (Wong, 2008). Studies conducted in the field of focus group interviews and data collection highlights that focus groups help to generate hypotheses that can be further tested using more quantitative approaches (Lewis, 2000). Diagnosing potential problems, programs, services, products, stimulate new ideas and result in frameworks for further validation with empirical research (Lewis, 2000). Because the characteristic of focus group interviews helps to investigate complex systems where the research may interact with the participants providing an opportunity to further ask for clarification questions it was appropriate to adopt for these research methods (Krueger 1988, p.18). Stewart and Shamdasani (1990) highlighted that convenience sampling may be employed for focused group interviews that consist of representative members of larger populations. Most focus groups interviews consist of between 6-12 participants (Stewart & Shamdasani, 1990). Krueger (1988) suggests that “the size of the group is governed by the objectives of the research as well. Smaller groups (4-6 people) are preferable when participants share information about the topic (Krueger, 1988, p.94). Krueger (1988) highlighted that the typical focus group interview might have up to 15 questions, depending upon the length of the interview and research objectives.

The results of the SLR (see Figure 2.12) defined the issues among the different layers of the IoT framework based upon different Precision Agriculture applications and used to generate the focus group interview questions. These questions were structured based upon the technical, operational, data management and finance barriers (cost, power consumption, communication range, data scalability, data storage, data interoperability, data processing, type of sensors, wireless communication technologies) identified from the IoT wireless sensors framework for precision agriculture applications identified in the structured literature review (see Figure 3.1).These questions are noted in the interview protocol in Appendix A.

In this study a purposive sampling was adopted (Kreuger 1988, p.94) to collect data from the SME''s involved in three focused groups interview sessions. The focused groups were categorized based upon the knowledge and expertise of the participants in three layers of IoT wireless sensors framework: 1. Perception layer, 2. Communication layer, 3. Data Processing & Application layer. The credentials of the participants, their current roles and expertise in IoT framework layer are highlighted in Table 3.2. The researcher contacted approximately 22 individuals out of which 18 participated (response rate of 81%) in 3 focused group interview sessions with 6 participants in each session. Each of the focused group consisted at least one expertise representing each layer of the IoT wireless sensor framework to reduce bias.

Research Question 3 (R3): How might a Lean and Green approach, in an Internet of things (IoT) wireless sensors framework be developed for the improved adoption of Precision Agriculture technologies among Indiana row crop producers?

Focused group interview data was analyzed by following a content analysis approach to understand and define decision variables related to barriers for answering the research question above.

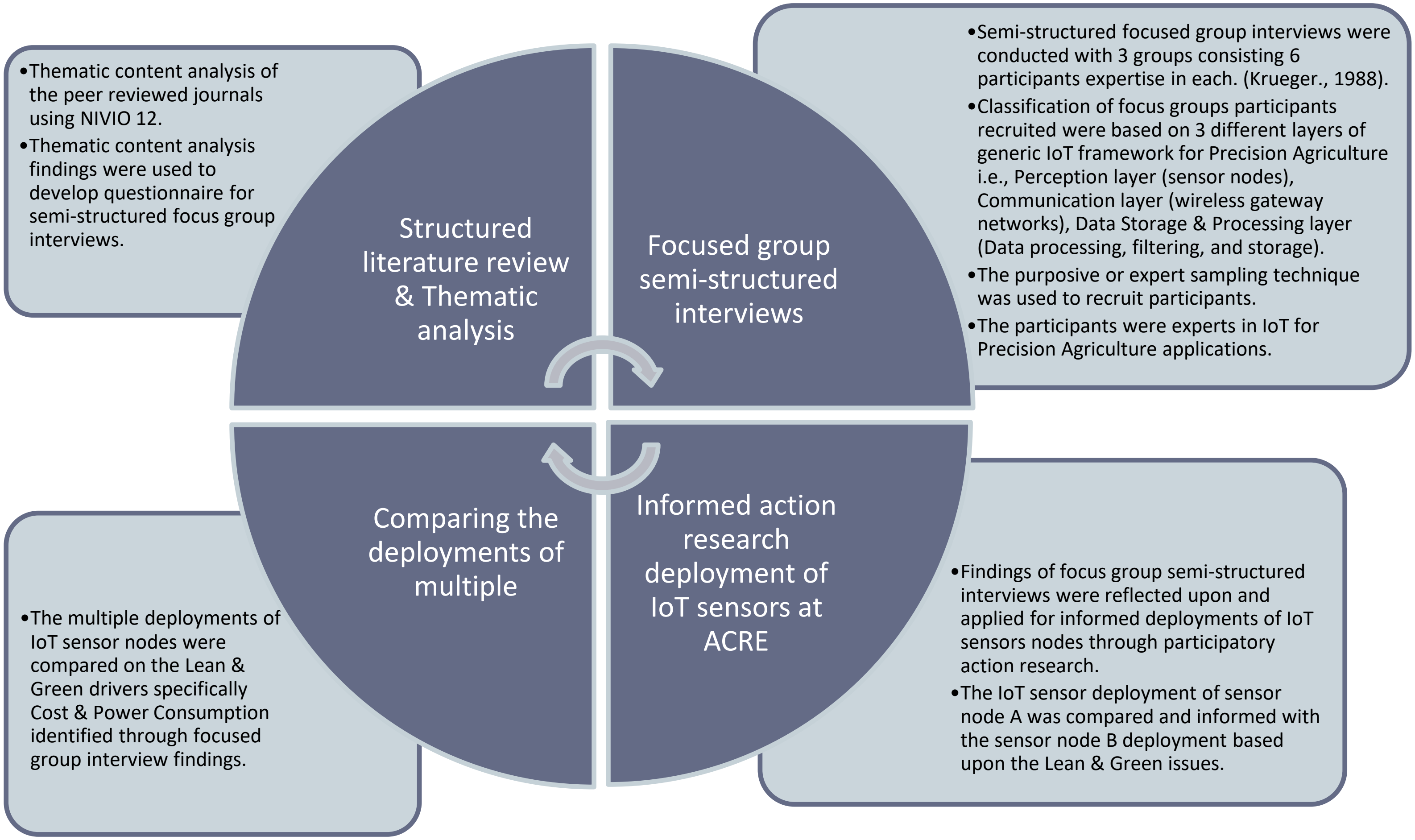


Fig. 3.2: Data collection methods focused group interviews following participatory action research cycle.

Table 3.2: Subject Matter Expertise (SME's)- focused groups interviews

Participants	**Current Role**	**Expertise in IoT wireless sensor framework layer**
Participant 1 (P1)	Digital Agriculture Technology Consultant	Wireless Communication technologies (Communication Layer)
Participant 2 (P2)	Program Coordinator in Agriculture Technology	Big Data Telematics, Data Analytics, Aerial Imagery (Perception Layer)
Participant 3 (P3)	Global Technology consultant	Wireless Communication technologies (Communication Layer)
Participant 4 (P4)	Graduate Research Assistant	UAV-aided wireless communication systems, Intelligent transportation system applications in Digital agriculture (Communication Layer)
Participant 5 (P5)	Precision agriculture technologies consultant and Farm-owner	Digital agriculture practitioner, Smart irrigation & Autonomous precision agriculture application (Application Layer)
Participant 6 (P6)	Academic Faculty	Wireless Communication Technologies for Agriculture, Signal processing, Sensor network design (Communication Layer)
Participant 7 (P7)	Cloud technologies consultant	Cloud computing platforms for Digital Agriculture (Data processing Layer)
Participant 8 (P8)	Graduate Research Assistant	Wireless Communication technologies, Embedded systems & edge-computing (Communication Layer)
Participant 9 (P9)	Academic Faculty	Decision Support System, Cloud Computing, Mobile Apps (Application Layer)
Participant 10 (P10)	Graduate Research Assistant	Autonomous precision agriculture applications (Application Layer)
Participant 11 (P11)	Digital Agriculture Consultant	Internet of Things (IoT) for Farm machinery autonomous applications (Application Layer)
Participant 12 (P12)	Graduate Research Assistant	Software engineering, API for crop monitoring applications (Data processing Layer)

Table 3.2: Continued

Participant 13 (P13)	Wireless communications Technology consultant	Wireless communication networking, Long range and wide area networks (LoRA) for digital agriculture applications (Communication Layer)
Participant 14 (P14)	Graduate Research Assistant	Internet of Things sensors applications for precision agriculture (Perception Layer)
Participant 15 (P15)	Extension program coordinator	Digital Agriculture practitioner, Rural area sensor networking (Perception Layer)
Participant 16 (P15)	Digital Agriculture practitioner & Farmer	Digital agriculture technologies adoption and practitioner (Perception Layer)
Participant 17 (P17)	Software engineer	Cloud computing, Big Data Analytics for IoT in Agriculture (Data processing Layer)
Participant 18 (P18)	Application Programming Interface (API) developer	Software developer for Precision agriculture applications, Cloud-back end (Data Processing layer)

3.3.2 Participatory Action Research Approach

The focus group interviews findings informed the deployments of a Precision Agriculture IoT based testbed through a participatory action research approach. Participatory action research is a collaborative process between researchers and participants to answer a critical inquiry focusing on a process of active learning (Baum, MacDougall & Smith, 2006). Participatory action research is based on data collection, reflection, and action (Baum et al., 2006). Participatory action research differs from conventional research as it enables action through a reflective learning cycle, whereby participants collect and analyze data, then determine the action to follow, utilizing decision variables (Kolb, 1984 & Tandon, 1996).

This research fits the criteria of participatory action research as the research questions of this study. Precision Agriculture IoT project at Purdue's Agronomy Center for Research and Education (ACRE) farm was being deployed. This study informed the ACRE deployment project by utilizing the generic participatory action research framework of Gray, Crawford, Lobo & Maycock (2019) to guide the deployment. The ACRE initial deployment is shown in Figure 3.3 below, representing generic technical, operational, data management and finance issues for an IoT deployment, called sensor node A in this study (Vasisht, Kapetanovic, Won, Jin, Chandra, Sinha, & Stratman, 2017). The initial deployment was informed by testing of IoT sensor node A for Precision Agriculture practices.

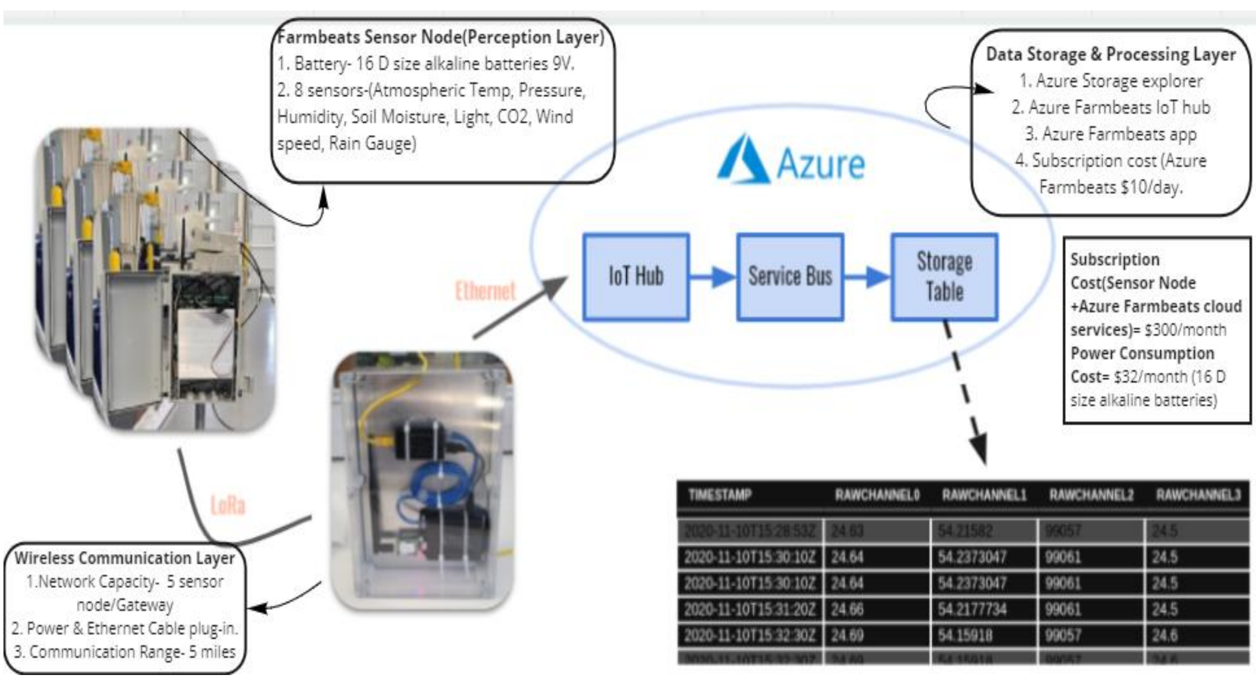


Fig. 3.3: Internet of Things (IoT) sensor node A- data pipeline

The ACRE IoT deployment, called sensor node B, was guided by critical design interventions identified and enacted upon by the researcher, guided by decision variables as participatory action research between the 1st deployment (sensor node A) and second deployment (sensor node B). The ACRE deployments of the initial (sensor node A) and redeployment (sensor node B) were then compared to Lean and Green performance drivers identified earlier.

3.4 Data Analysis

This section highlights the data analysis techniques i.e., content analysis of focused group interviews, Interpretive Structural Modeling (ISM) and comparison of participatory action research deployments of sensor nodes.

3.4.1 Coding & Thematic analysis of Focused-group interviews

Data analysis is the part of qualitative research that mostly distinctively differentiates from quantitative research methods. Qualitative data analysis is a more dynamic, intuitive, and creative process of inductive reasoning, thinking, and theorizing (Basit, 2003). Data analysis in qualitative research is defined as the process of systematically searching and arranging the interview transcripts. The process of analyzing qualitative data involves coding or categorizing of data, which reduces the volume of raw information followed by identifying significant patterns drawing meaning from the data, developing a logical chain of framework, or adding to grounded theory (Tashakkori & Teddlie, 2009). NVivo coding software was used to code the data from interviews. Inter-reliability of the coding thematic analysis of the data was checked with another rater to ensure the reliability kappa value $k > 0.70$ for acceptable reliability.

3.4.2 Interpretive Structural Modeling (ISM)

The nodes emerging from the interviews were analyzed for pairwise relationship comparison to develop a framework model. The Interpretive Structural Modeling approach first proposed by Warfield in 1973 (Warfield 1974a, b; Sage 1977) to analyze the complex socioeconomic systems. Interpretive structural modeling may be defined as a process that transforms unclear mental models of systems into visible well-defined models for adoption purposes. Interpretive Structural Modeling (ISM) can also be used for identifying and summarizing the relationships among specific variables which defines a problem or an issue (Sage 1977; Warfield 1974a, b). ISM provides a means by which order can be imposed on the complexity of such variables (Mandal and Deshmukh, 1994). There are multiple applications of ISM in many areas the majority which are in decision support systems (Hansen, Mckell & Heitger, 1979), waste management (Sharma and Gupta, 1995), vendor selection (Mandal and Deshmukh, 1994), product design, supply chain management (Agarwal et al., 2007), decision making (Lee, 2008), value chain management (Mohammed, Shankar & Banwet, 2008) and world-class manufacturing (Haleem, Sushil, Qadri & Kumar, 2012). The steps involved in the ISM approach utilized in this study are described in the literature and shown in Figure 3.4 (Malone, D. W. 1975; Govindan et al. 2015; Agrawal, A. 2020).

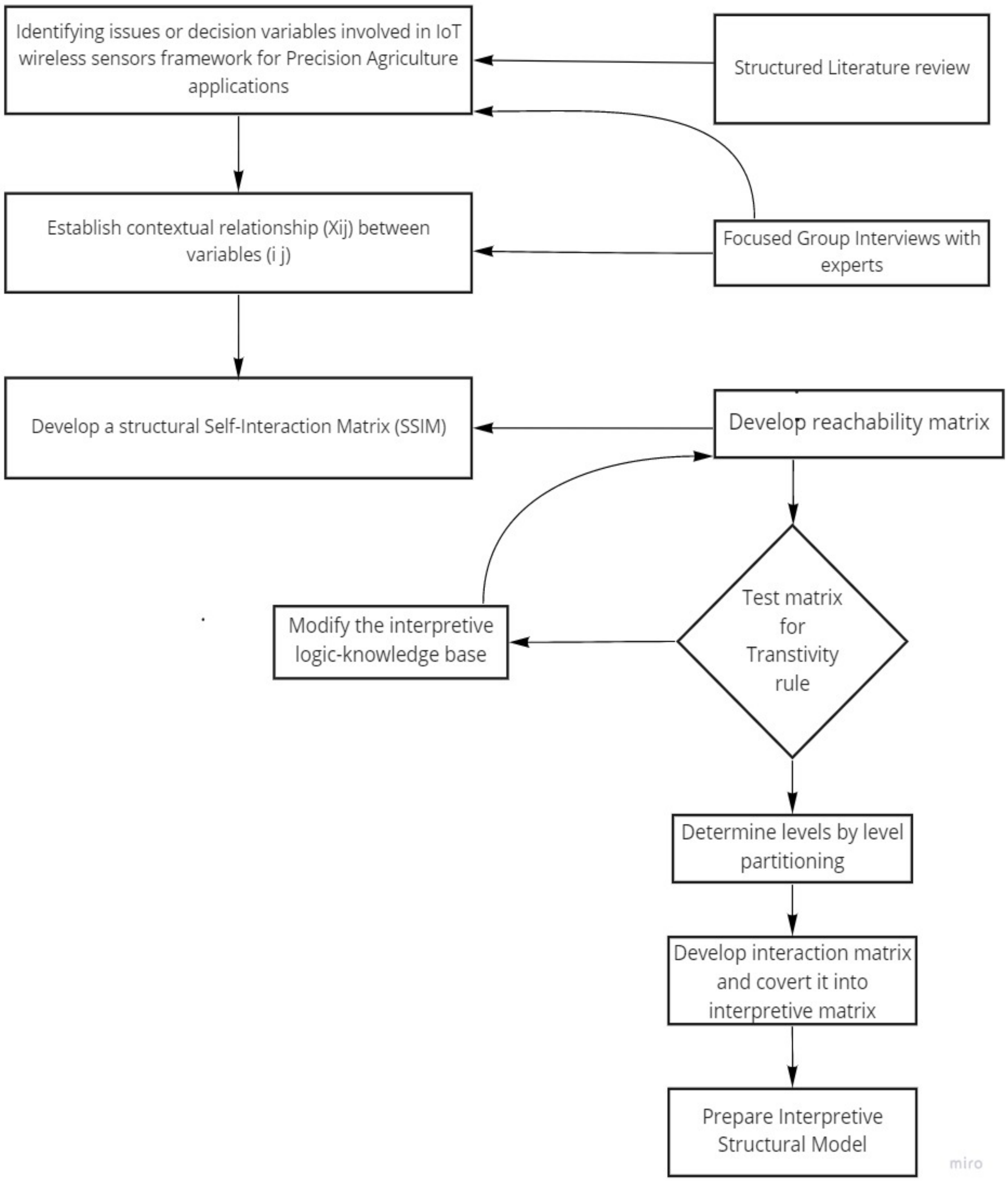


Fig. 3.4: Interpretive Structural Modeling Methodology for this study
Malone, D. W. 1975, Govindan et al. 2015, Agrawal, A. 2020

The steps involved in the ISM approach are described as follows in the context of this research study:

1. Organize a group of experts for interviews and defining variables: In this study, focused group interviews were organized with a group of expertise based on three layers of IoT wireless sensors framework, 1. Perception layer, 2. Communication layer, 3. Data storage & processing layer to define themes and variables validated by the SLR in context of barriers pertaining to participatory action research decision variables in IoT wireless sensors framework.
2. Identifying variables for finding contextual relationships: The focused group interview data was analyzed to identify the decision variables and contextual relationships from the barriers identified by the focus group interviews. Eleven variables were identified and defined through content analysis findings of the interviews for a Lean-Green IoT wireless sensors framework.
3. Developing structural self-interaction matrix: Through the analysis of the three focused group interview sessions 6 participants each, total n=18 participants a structural self-interaction matrix was created with descriptive contextual pairwise relationships defined among the 11 variables identified in the prior step.
4. Developing reachability and interaction matrix: A random sample of at least 3 participants from the group of 18 participants were contacted again to validate the contextual relationships defined in the matrix and developing a reachability matrix identifying transitivity (e.g., indirect relationship- if A is related to B directly & B is related to C then A is in transitive relationship with C) relationships between variables was created.
5. Developing interpretive structural model: The reachability matrix i.e., the outcome of previous step (4) was decomposed to create structural models. This was an interactive process in which the 11 variables identified in step 2 were classified in different cluster levels, based upon their driving and dependence power calculated for each variable in step 4.

3.4.3 Comparison of action research deployments

The findings from the interviews defined the decision variables used to intervene and compare deployments at ACRE. The performance of deployments (sensor nodes A and B) at

ACRE were compared, based on the Lean and Green performance drivers of cost, power consumption, data interoperability & data scalability identified from the SLR and validated through content analysis of the focused group interviews. The action research deployment comparisons also partially validate the Interpretive Structural Model constructed for the Lean and Green IoT wireless sensors framework.

3.5 Reliability & Validity

Interpretive Structural Modelling was used for data analysis, based on the decision variables identified in the three generic layers of Internet of Things (IoT) wireless sensors framework. Construct validity, internal validity, external validity, and reliability were important issues in overall research design (Yin, 2002; Voss, Tsikriktsis & Frohlich, 2002). Construct validity means that the operational measures used to translate the constructs measures the concepts that they are meant to measure (Yin, 2002). In the context of this study, the construct validity were the operational definitions of the decision variables identified from the interviews. Internal validity means that the study measures the demonstrated relationships and are explained by contextually validated expert opinion. For the internal validity in the three focused group interview sessions, three participants were randomly selected, per the typical practice in ISM (Malone, D. W. 1975; Govindan et al. 2015; Agrawal, A. 2020) to fill-out a matrix survey developed from the initial interview data coded in NVivo software. The filled-out survey by three Subject Matter Expertise (SME's) chosen from focused group interviews panel was validated and checked for reliability (consistency) of initial self-interpretation matrix developed by researcher from analysis of interview data. External validity means that the results are valid in similar settings outside the studied objects. Reliability means that the study is objective meaning other researchers could reach the same conclusions in the similar settings. Further to assure validity and reliability of the research design, a triangulation method was used, a typical practice for rigor in qualitative research methodologies (Mathison, 1988; Singleton & Straits, 1999). Triangulation may involve combining multiple data sources (data triangulation), using multiple research methods to analyze the same problem (methodological triangulation), or using multiple investigators. In this study, the approach of triangulation was followed by the researcher collecting and analyzing data from different sources i.e., the SLR (n=70), and the three focused group interview sessions. The content analysis from the focused group interviews was triangulated by three non-subject matter expertise appraisers for inter-reliability. The theoretical framework developed through Interpretive Structural Modeling was partially empirically validated by comparison of action research deployments using multiple linear regression analysis of the real time performance data from the deployments. The comparison of IoT deployments was based on the Lean and Green drivers i.e., Cost, Power consumption, Data interoperability, Type of wireless communication, Data storage and Data scalability identified from the content analysis. The following chapter describes the findings for the focused group interviews, Interpretive Structural Model results and performance comparison of action research deployments.

CHAPTER 4. RESULTS

This section describes the thesis findings for Focused group interviews, ISM, and comparison of action research deployments.

4.1 Focused group interviews content analysis

The data gathered from the three focused group interview sessions is shown in Table 4.2. The participants questions in semi-structured interview scripts are in (Appendix A). The interviews were conducted virtually and recorded with the informed consent of participants following IRB guidelines and protocol. The participants were asked to respond voluntarily each question with follow-ups for clarifications. Transcriptions of the recorded interviews generated were uploaded and analyzed in text files format using NVivo 12 software. Text search queries pertaining to Lean and Green issues are highlighted in the interview questions, based upon the research objectives (see Appendix A) and entered using the keywords "Cost", "Power consumption", "Scalability", "Communication range", "Data latency", "Data storage", "Data processing", "Data interoperability", "Wireless communication technology", "Type of sensors", "Monitoring row crop diseases", "Autonomous", "Smart Irrigation", "Smart Fertilization", "Farm machinery navigation", "Precision Applications" and string "OR" was used to connect keywords for broader search criteria ensuring holistic coverage for content analysis.

4.1.1 Nodes (Content analysis) & Inter-reliability test

The query results from the previous section were analyzed, creating nodes for each of the variable relationship identified. Nodes were developed by analyzing the focused groups data following a thematic content analysis approach. The preliminary nodes identified by the researcher were compared for inter-reliability, with 3 raters per, typical practice for reliability (Hruschka et al., 2004). The three raters include researcher, and two other researchers, with non-subject matter knowledge, but with expertise in content analysis, for minimizing bias (Tashakkori & Teddlie, 2003). The non-subject matter expertise raters have proficiency conducting content analysis using NVIVO. A codebook was generated from NVivo software highlighting the list of nodes describing relationships between decision variables identified through content analysis. The Kappa values from inter-reliability test are highlighted in Table 4.1. Cohen's Kappa coefficient is a statistical measure of inter-rater reliability, which many researchers regard as more useful than the percentage agreement, since it considers the amount of agreement that could be expected to occur through chance (Sotiriadou, Brouwers & Le, 2014). NVivo calculates the Kappa coefficient individually for each combination of node and source. If the two users are in complete agreement about which content of the source should be coded at the node, then the Kappa coefficient is 1. If there is no agreement between two users (other than what could be expected by chance), the Kappa coefficient is ≤ 0. A value between 0 and 1 indicates the scale of agreement. The Kappa (k) value ≤0.40 means weak agreement, between 0.40-0.75 good agreement, above 0.75 excellent agreement (Sotiriadou, Brouwers & Le, 2014). The average kappa (k) value is calculated for each individual node by using the mean k value calculated for each comparison rating between individual raters (n=3 raters) involved as per the typical practice highlighted in the studies (Tashakkori & Teddlie, 2003, Hruschka et al. 2004).

Table 4.1: Nodes & Inter-reliability (Kappa) test results

Nodes (Variable relationship)	**Kappa 1 (Raters 1-2)**	**Kappa 2 (Raters 1-3)**	**Kappa 3 (Raters 1-2,3)**	**Avg-Kappa**	**Agreement (%)**
Data interoperability- Data processing	0.4392	0	0.4392	0.293	96.91
Data interoperability- Data storage	0.4901	0	0.4901	0.33	98.57
Data interoperability -Type of sensors	0	1	0.3162	0.44	96.96
Data interoperability- Type of Wireless communication	0	1	1	0.67	95.18
Data interoperability-Type of Precision application	1	1	-0.0349	0.65	100
Data Latency- Autonomous applications	0	1	0	0.33	97.57
Data Latency- Autonomous applications (2)\Data latency-Monitoring Precision applications	0	1	1	0.67	95.1
Data Latency- Autonomous applications (2)\Smart Fertilization-Data Latency	1	1	0.2441	0.75	100
Data Latency- Autonomous applications (2)\Smart Irrigation-Data Latency	0	1	-0.0077	0.33	98.17

Table 4.1: Continued

Data Latency- Autonomous applications\Data latency- Monitoring Precision applications	0.2441	0	0	0.0814	94.24
Data Latency- Autonomous applications\Farm Machinery- Data latency	-0.0077	0	0.4111	0.67	98.43
Data Latency- Autonomous applications\Smart Fertilization- Data Latency	0	0	0	0	98.45
Data latency- Data scalability	0	1	0	0.67	92.23
Data latency-Autonomous	1	0	1	0.75	100
Data latency-Sensor monitoring	1	0	0	0.33	100
Data latency-cost	1	1	-0.0192	0.0814	100
Data Processing- Data latency	-0.0192	0	1	0	95.45
Data processing-Communication range	1	1	1	0.33	100
Data Scalability- Power consumption	0	0	0	0	97.3
Data Scalability-Cost	1	1	1	0.67	100
Data storage - Cost	1	1	-0.0088	0.660	100
Data Storage- Data latency	0	0	0	0	99.62
Data Storage- Data Processing	-0.0088	0	-0.0096	0.327	97.46
Data Storage- Data Scalability	-0.0096	0	1	1	97.98
Data storage- Type of Precision application	0	0	0	0	97.52
Data Storage-Power consumption	1	1	-0.0142	1	100
Power consumption-Data latency	-0.0142	0	1	0.66	92.44
Sensors locations\Phone devices	1	0	0	0.33	100
Sensors locations\Soil	1	0	0	0.66	100
Smart fertilizing	1	0	0	0.3286	100
Type of Precision Agriculture Application- Data scalability	0	0	0	0.67	99.25
Type of Sensor - Data storage	-0.0115	0	0	0	96.77

Table 4.1: Continued

Type of Sensor - Type of Wireless Communication	0	1	1	0.33	96.84
Type of sensor -Cost	1	1	0	0.67	100
Type of Sensor- Data Latency (2)	0	1	0	0.33	99.56
Type of sensor- Data processing (2)	0	1	-0.031	-0.004	97.26
Type of sensor- Data scalability	1	1	0	0.67	100
Type of sensor- Farm Machinery-Autonomous	-0.031	0	1	0.67	92.47
Type of sensor- Farm Machinery-Autonomous (2)\Accelerometer	1	1	1	0.67	100
Type of sensor- Farm Machinery-Autonomous (2)\GPS	1	1	0	0.67	100
Type of sensor- Farm Machinery-Autonomous (2)\Sound	1	1	0	0.33	100
Type of sensor- Farm Machinery-Autonomous\Accelerometer	0	0	0	0	99.17
Type of sensor- Farm Machinery-Autonomous\GPS	0	0	0	0.323	99.67
Type of sensor- Farm Machinery-Autonomous\Sound	0	0	1	0.67	99.52
Type of sensor- Monitoring row crop diseases	1	1	0	0.67	100
Type of sensor- Monitoring row crop diseases (2)\Environmental	0	1	1	1	97.01
Type of sensor- Monitoring row crop diseases (2)\Remote sensing	0	1	0.2636	0.67	98.39
Type of sensor- Monitoring row crop diseases (2)\Site-specific	1	1	-0.0058	0.67	100
Type of sensor- Monitoring row crop diseases\Environmental	0.2636	0	1	0	97.43
Type of sensor- Monitoring row crop diseases\Remote sensing	-0.0058	0	0.1343	0	98.04
Type of sensor- Power consumption- Monitoring application	0.1343	0	0	0	92.1
Type of sensor- Power consumption- Monitoring application (2)	0	1	1	0.67	91.43

Table 4.1: Continued

Type of sensor- Power consumption- Monitoring application (2)\Sensor power monitoring	0	1	0.797	0.67	99.31
Type of sensor- Power consumption- Monitoring application (2)\Sensors Power autonomous	1	1	0	0.42	100
Type of sensor- Power consumption- Monitoring application\Sensor power monitoring	0.797	0	0	0.66	99.65
Type of sensor- Power consumption- Monitoring application\Sensors Power autonomous	0	0	1	0.42	99.33
Type of sensor- Smart fertilization- Autonomous (2)	1	1	1	0.67	100
Type of sensor- Smart fertilization- Autonomous (2)\Remote sensing	1	1	0	0.67	100
Type of sensor- Smart fertilization- Autonomous\Ph nitrate	1	1	1	0.60	100
Type of sensor- Smart fertilization- Autonomous\Remote sensing	0	0	1	0.67	99.43
Type of sensor- Smart Irrigation- Autonomous	1	1	1	0.26	100
Type of sensor- Smart Irrigation- Autonomous\Soil moisture	1	1	1	1	100
Type of sensor-Communication range	1	1	0	1	100
Type of sensors\Audio	1	0	0	1	100
Type of sensors\Autonomous	1	0	0	0.33	100
Type of sensors\Carbon Sensors	1	0	0	1	100
Type of sensors\Environmental sensors	1	0	1	1	100
Type of sensors\Microbial Sensors	1	0	0	0.67	100
Type of sensors\Monitoring crop disease	1	1	0	0.67	100
Type of sensors\Monitoring crop disease\Remote sensors	1	0	0	0.33	100
Type of sensors\Satellite	1	0	0	0.33	100

Table 4.1: Continued

Type of sensor-Type of Wireless Communication	0	0	0	0.67	99.08
Type of Wireless Communication-Autonomous application	0	0	0	0.33	99.27
Type of Wireless Communication-Communication range	0	0	0	0.67	98.85
Type of Wireless Communication-Data Scalability	0	1	-0.0137	0.33	94.55
Type of Wireless Communication-Monitoring application	-0.0137	0	0.385	0.33	97.2
Type of Wireless Communication-Power consumption	0.385	0	0.2408	0.2086	95.05
Type of Wireless Communication - Data Latency	0.2408	0	-0.0128	0	91.83
Type of Wireless Communication - Data storage	-0.0128	0	0	0.33	94.6
Type of Wireless Communication - Cost	0	1	0	0.124	96.78
Types of Sensor- Data Quality	0	1	1	0.2086	96.65

The nodes highlighted in the Table above, with average Kappa value of 1 meaning excellent agreement are Data storage- Data scalability, Data storage- Power consumption and Type of sensor- Communication range. Nodes having good agreement with average Kappa value of 0.67 are Data scalability- Cost, Data storage- Cost, Power consumption- Data latency, Data latency- Autonomous application, Data latency- Data scalability, Type of sensor- Power consumption, Type of sensor- Data scalability, Type of wireless communication- Communication range. Nodes having week agreement with average Kappa value of 0.33 are Data processing- Communication range, Type of wireless communication- Data storage, Type of wireless communication- Data scalability and Type of sensor- Type of wireless communication. Nodes having very week agreement with average Kappa value of less than 0.33 are Data interoperability- Data processing, Type of sensor- Data processing, Type of sensor- Data storage, Data storage- Type of Precision application and Type of sensor- Data quality. Week agreement doesn't mean the nodes are insignificant for relationships and were further validated in this research using Interpretive Structural Modeling approach. All node relationships are described in the following section through descriptive content analysis approach.

4.1.2 Descriptive content analysis

A codebook was developed after performing the inter-reliability and shown in Table 4.2. highlighting the participants actual response quotes, coded under the respective nodes using NVivo from interview transcription data. The average inter-reliability Kappa (k) value calculated for each node is shown, along with descriptive analysis highlighting the relationships between the variables coded for the respective node. The descriptive analysis was subsequently used to create the decision variables for the participatory action research process in ACRE redeployment and are shown in Table 4.3. The descriptive analysis was used to develop a self-interaction matrix (see Figure 4.1) which highlights the contextual relationships between variables for developing the interpretive structural model (ISM) framework.

Table 4.2: Descriptive content analysis

Nodes (Variable relationship)	Participant response	Avg. Kappa value (Inter-reliability)	Descriptive Analysis
Data interoperability-Data processing	**P1:** "So, I'll touch on it from a different angle. You know from a practicality perspective, from a true adoption in the field, people using this, there's probably data **interoperability** in solving." **P2:** "How will people communicate? Common data from company sensor, sensor, business, business, whatever is probably more important right now. At least then the technical specifications of the type of database you're using or how you're storing or how you're **processing.**"	0.30 (Weak agreement)	**Data processing** requirements don't directly depend upon the **Data interoperability** rather it depends upon the type of precision agriculture application, data latency and communication range requirements.
Data interoperability-Data storage	**P2:** "You know **interoperability** of formats and everything, something that will happen as add data gets larger and larger is that you know you might want to go between different cloud environments, so we have some technology that we are developing to do some of that not entirely pivoted to other, **but multi cloud** is for example Thing to do, it's kind of tangentially related." **P3:** "**Data interoperability** it's more at the software like application level. It's like when you deal with issues like that. Different **software** companies may need to talk to each other to make sure the. Results generated by them can be used by each other."	0.33 (Weak agreement)	**Data storage** depends upon the data interoperability requirement. The interoperability between sensors, wireless communication technologies and **cloud storage end.** The requirements for storage less or more depend upon the compatibility of storage (sensors, wireless communication gateway, cloud) with each other and **precision agriculture application requirements**.

Table 4.2: Continued

Data interoperability -Type of sensors	**P4:** "If I install **sensor A** and now, I'm stuck with this product and I can't use this one over here because they just don't talk to each other, you know? I mean like if we're really going to get people to adopt this stuff, there needs to be choice and it needs to be some **flexibility**." **P5:** "**Data interoperability** is going to be. It's really important to find it's a very hard thing to define. You've seen things like at Gateway. Try and maybe they went too far and got really specific in the weeds. There's probably some middle ground. You know that that needs to be the first step. It's like how do we identify the 90% most **important data and just come up with formats for** that?"	0.44 (Fair Agreement)	**Data interoperability** depends on the type of sensors as interoperability means data coming from different types of sources. As, the participant reported that there will be more data interoperability between the same category of **sensors** as they get integrated well with a particular type of wireless communication protocol (LoRA, Zigbee, Sigfox, BLE, Wi-Fi, GPRS 3G/4G).
Data interoperability-Type of Wireless communication.	**P2:** "I think open source obviously has its own benefits, right. There is the NB- IoT is definitely nice. You can have NB IoT tier towers, but it is more expensive. I think I know that they are connected by doing Laura van connectivity which will be nice. It will have this **open source** thing in addition to if you want. Parts of proprietary technology." **P5:** "As long as this server has the ability to talk to the sensor using **the correct wireless communication technology, it doesn't matter much like which technology you are using.** Their communication. Just establish the link and the data flows along the link so in that sense the communication is like a very low level, almost like you don't need to worry about it as long as it's there. OK yeah, and for data **interoperability** it's more at the software like application level."	0.67 (Good Agreement)	**Type of wireless communication technology** doesn't depend upon the data interoperability and vice versa. The participants highlighted that Data interoperability is more adaptable at the user-interface i.e., **software or cloud storage end.**

Table 4.2: Continued

Data interoperability-Type of Precision application	**P6: "Annotated data** set so that you can exactly find out what is the disease and you can use that annotated data set into training your different machine learning or deep learning model. So that is one of the missing pieces, because although we. We reached out to Plant Village plant dog datasets, but then we had to do the annotation by ourselves. So, a very large scale annotated data set is still needed and that is 1 area. I'm hoping that more and more generals will be inspiring the researchers to really share their data." **P7:** "Flow rate, pressure, **pH of that** so that it is very hard to join that piece of information. The Fertilizing team for the different sections of the farm. So as previously mentioned, integrating like different **heterogeneous sensors."**	0.67 (Good Agreement)	**Data interoperability** depends upon the type of precision agriculture application, type of sensors and cloud data storage user-interface. For instance, as the participants highlighted that for monitoring row crop diseases application of **open-source field topography, soil and satellite data apart from the sensors** can be used easily to develop robust row- crop disease models. Also, for autonomous applications such as smart irrigation and smart fertilization the data interoperability between soil moisture, **Ph, nitrate** and open-source topography, soil data can be useful to develop robust models for sending alerts.
Data Latency-Autonomous applications	**P4:** "Depending on how latency sensitive that specific activity is, and in general I don't think the **latency** thing is ever at the millisecond level or the second level. It's always at a higher level of granularity because you know if you're like sensor monitoring, for example **soil monitoring.** I'm like the comparison that I'm making is compared to self-driving cars or what have you and hear others may be able to chime in if you have like a **self-driving tractor** then I guess some of the latency sensitive mapping from the self-driving car industry comes in where you might have to do on device analytics to take care of that latency issue." **P3: "Drone that is sensing and at the same time spring** then I think it becomes important to at that sub millisecond level that you would actually have to do the computation."	0.75 (Excellent Agreement)	**Autonomous applications** have **low latencies in milli-seconds or seconds** especially Farm machinery navigation systems using GPS and accelerometer sensors. The smart irrigation and smart fertilization where the data from soil moisture, Ph and Nitrate sensors have **data latencies requirements in minutes or hours as participants reported. The monitoring applications** specifically for row crop diseases where **days and weeks might be the data latency requirements.**

Table 4.2: Continued

Data latency-Monitoring Precision applications	**P4**: "I think more of the typical **agricultural applications have a greater bandwidth intensive latency** where it does not have to be at **the second level, it can be at the minute level or hour level."** **P5:** "Amount of **agronomic data is often not very latency sensitive**, you know, I mean. Days might start being a problem in weeks, probably our problem. If **you're going to act out of a millisecond,** certainly not a big deal, but I do think as you start seeing." **P4**: "If there is **remote sensing** or otherwise you know yes there is **time to move that to the right place.** Do the computation, generate the prescription and then send it out."	0.67 (Good Agreement)	**The monitoring applications** specifically for row crop diseases where **days and weeks** might be the **data latency** requirements as reported by the participants.
Data Latency-Farm Machinery	**P6: "Automation in vehicles** and equipment and sprayers and things like that. You do have this sort of **local.** But, also increasingly there are machines that on the front of the machine they sense what needs to happen here and on the back of the **machine it happens so in that case there really is no latency** like it's. You know it's gotta be within a **fraction of a second."**	0.67 (Good agreement)	The **autonomous precision applications** have **low latencies in milli-seconds or seconds** especially Farm machinery navigation systems using GPS and accelerometer sensors.

Table 4.2: Continued

Data Latency-Smart Fertilization	**P7: “Days** might start being a problem in weeks, probably our problem. If you're going to act out of a **millisecond**, certainly not a big deal, but I do think as you start seeing. **Automation and autonomy in vehicles and equipment and sprayers and things like that.** You do have this sort of **local analytics processing** problem that does have latency issues.” **P9:** Drone that is **sensing and at the same time spring then I think it becomes important to at that sub millisecond level** that you would actually have to do the computation.”	0.75 (Excellent Agreement)	The smart irrigation and **smart fertilization where** the data from soil moisture, Ph and Nitrate sensors have **data latencies requirements in minutes or hours** as participants reported. The **monitoring applications specifically for row crop diseases where days and weeks** might be the data latency requirements.
Data Latency-Smart Irrigation	**P8:** “If you had some sort of censored on your **irrigator** that could you know spray based on, you know based on sensor readings. Of course, **irrigators** are not moving **100 miles an hour,** but you probably do need to be able to make decisions here faster than a second or something like that. And we are starting to see that you know. I remember there's a laser-based weed. You know that you put on a boom and it actually it's the weeds with the **laser you know, and that's a lot of image processing.”**	0.33 (Weak agreement)	**Data latency** requirements for the smart irrigation applications might be in **minutes or hours** that medium latency requirement higher than farm machinery autonomous applications but lower than monitoring row crop diseases biophysical applications.

Table 4.2: Continued

Data latency-Data scalability	**P7:** “If there is **remote sensing** or otherwise you know yes there is time to move that to the right place. Do the computation, generate the prescription, and then send it out. But, also increasingly there are machines that on the front of the machine they sense what needs to happen here and on the back of the **machine** it happens so in that case there really is no **latency** like it's. You know it's gotta be within a fraction of a second depending on the speed of the vehicle, certainly anything that's navigation related if it's **autonomous,** has to be **sub millisecond.”** **P8:** “So, for **autonomous applications** one of the nice things is for you to know if you're thinking of autonomous driving in terms of tractors or whatever, you can have a lot of data and you can offline train the model right. So if you can train the model offline using various kinds of temporal datasets that have been taken overtime, it's going to just enable decisions to be taken at real time faster and. Currently it is right you don't want it to make bad decisions, especially for things related to autonomous driving, so I think things **were latency, it's latency sensitive and plus the cost of a bad decision is high.”**	0.67 (Good Agreement)	**Data latency** doesn’t depend upon the data scalability requirements as it depends upon the type of **precision agriculture application requirements.**
Data latency-Cost	**P9:** “If you get, you know that data all the time and then you know if you want to record with ice Blue. If you want your **real data at the end of the year,** you know you don't need that. By the 2nd, get that at the end of the year, you know that the high bandwidth data you don't necessarily need you know. And you also need to consider the cost of running a streaming device running on cell data because you have to pay a monthly charge **and that might be 60 bucks to hundreds of dollars.”**	0.10 (weak agreement)	**Data latency** doesn’t depend upon the cost requirement rather it depends upon **the type of precision agriculture application.** As one of the participants reported that for monitoring row crop diseases application data from the remote sensing image sensors can be transferred to cloud storage at higher latencies depending upon the criticality of timeline developing predictive models.

Table 4.2: Continued

Data processing-Data latency	**P8: “Low latency** links back to some **major processing,** but edge computing I think is still going to be a key element in advancing some of these technologies.” **P9:** “So if you're concerned about **latency** you might want to do **more of the processing** on the device or on the edge or in the cloud depending on the latency requirements to decide how much to transfer the model? For example, **Cloud** will give you most accuracy, maximum accuracy and you can use very beefy models that are pre-trained, but you might not be able.” **P8:** “So, I think depending on whether it's an autonomous application or it's a **by-physical application** and autonomous, a lot of data will be good because you can take advantage of **offline training the model and having a model that is updated once in a while.”**	0.10 (weak agreement)	**Data processing** does depend upon the data latency requirements. For **the lower latency** requirement of autonomous applications such as Farm machinery efficient navigation most of the data process takes **place at the Wireless communication gateway edge end.** However, for monitoring row crop diseases applications where data latency requirements are higher the data can be processed **overtime on the cloud storage end to develop application programming interfaces for row-crop diseases** predictive models.
Data processing-Communication range	**P10:** “I'm not an expert here, but aren't there also examples where **you're storing the data on the device or at the edge** and you're only sending alerts or notifications if something is out of range, so then that limits your. You know the communications requirements, so there's ways again around finding what you're trying to do. You may only need to **send short bytes of data with an alert or a notification when it goes out of range.”**	0.33 (weak agreement)	**Data processing** depends upon the communication range between sensor node and **wireless communication technology,** low latency autonomous applications such as autonomous farm-machinery efficient navigation for harvesting or seeding using GPS, accelerometer or autonomous drones might require a lot of **local data processing** at **the wireless communication gateway edge end with lower latencies.**

Table 4.2: Continued

Data Scalability-Power consumption	**P10:** "So, running the analytics locally or at the edge will require some adaptation to the neural network in order to run them within your essay. So, when you're **transferring to the back end,** if your content is too complex, you don't want to constantly try to transfer a major amount of data, you don't want to hog the bandwidth. By **continuous transfer. So, it's not only the latency and power requirement,** it's also the amount of data."	0.33 (weak agreement)	**Data scalability** depends upon the **power consumption** requirements as large numbers of different types of sensors to increase data scale or using remote sensing **drone imagery sensors can consume more power and increase costs significantly.**
Data Scalability-Cost	**P7:** "You know that's kind of application specific need, but I could definitely see you know if the data **LoRA** is what you have here in this presentation slide, I can definitely see that being useful. If you get, you know that data all the time and then you know if you want to record with ISO-Blue. If you want your real data at the end of the year, you know you don't need that. By the 2nd, get that at the end of the year, you know that the **high bandwidth** data you don't necessarily need you know."	0.70 (Good Agreement)	**Data scalability** depends upon the cost requirements as data from larger & different types of sensors deployed in different areas of the field require **more storage capacity that involve costs**. However, the increase in storage at the cloud end or wireless communication gateway edge doesn't **contribute to significant increase in costs as participants reported.** Installing more and different types of sensors to scale contributes much to the variable input cost.
Data storage - Cost	**P10:** "So that's not something that **I think should be a huge priority on the cloud side especially.** Sir, keeping terabytes of data costs next to nothing on the cloud side or on the edge side. I'm sorry, probably a little more important are the I work on a project called Iso- Blue, which is an edge computing device on agricultural machinery." **P8:** "We have 500 gigabyte SSD's on him that **doesn't cost too much and is smaller than a credit card,** so that's more than enough for us for a couple of seasons of data and you could go much bigger without having any issues. Obviously, it will cost a little more, but in the grand scheme of things, I don't think that's super."	0.67(Good Agreement)	**Data storage** requirements depend upon the cost. However, increasing the data storage requirements at the **cloud storage and wireless gateway edge doesn't cost much as reported by the participants.**

Table 4.2: Continued

Data Storage-Data latency	**P7:** “Wi-Fi has short to medium coverage, **LoRa has really long coverage** and for many applications in agriculture, the **latency doesn't matter much. For example, when you monitor the condition of soil,** you may be able to cache the data and send the data through a slow link. Just **gradually over time,** also you can also send it over time like it's not required as the **interval is very large.** Yeah, in that case you have more things you can. Work with, for example. Some people say even if you are using it. Some short-range technologies on the sensor side. You may be able to catch the data and then collect it.” **P10:** “By **driving cars with connections to the sensors, just like physically collecting the data nearby, you go there with some connection to collect the data.** In that case the **circular built is more like if we want to scale the case you need to manually go there somehow, but you can scale to areas where there's no connection at all.”**	0.33 (weak Agreement)	Data storage depends upon the **data latency requirements. The participants highlighted that higher the data latency** for monitoring application more **data storage is required at the cloud-storage end for storing data overtime with LoRA at higher latencies** to build disease predictive models.

Table 4.2: Continued

Data Storage-Data Processing	**P7: "**Running the **analytics locally or at the edge will require some adaptation to the neural network** in order to run them within your essay. Pounds write latency, bumps, and the other is transferred to the back end, right? So, when you're **transferring to the back end."** **P8: "**As a researcher, it pains me, but I think the reality is that you know big data and these types of processing ideas are going to make lots of cheap sensors. Then maybe you don't know they're not scientific if you will, and they don't update every second. But there are lots of them. A lot more valuable than one or two really fancy ones. Or you know that meaning that oftentimes **the cheap ones are also lower power,** and you know, because you're not necessarily looking for the same type of tolerances and things. I think there's also a practical advantage there in that. Go out and visit a farm, right? Even if you're not a farmer, **gotten into farming or you know this doesn't take very long to realize that things break. Everything is far apart, it is very hard to maintain this stuff. You know you're a lot better having 1000 tons** and letting under break than having two."	0.33 (Weak agreement)	**Data storage** depends upon the data processing requirements. The participants reported that for the Autonomous application such as Farm machinery navigation, smart irrigation & smart fertilization the **Data processing is required at the wireless gateway edge end and therefore storage requirements goes accordingly.** For monitoring row-crop diseases application the data can be processed for developing predictive models on the cloud-storage end where **data can be stored from different gateways & other open-public data sources overtime.** The vice versa is not true because data processing depends upon the type of precision agriculture application and not on data storage requirements.
Data Storage-Data Scalability	**P10:** "Always assume that the data can always be immediately sent and therefore the ability of the **local sensor** to buffer, to store a certain amount of information until it reaches back coverage is useful." **P8:** "I was going to say that's seems to be the trend to capture as much data as possible at the edge. So really, rather than just applying the technology randomly trying to look at what's **the purpose of the data,** as you've all said."	1 (Excellent agreement)	Data storage depends upon the data scalability requirements. **Higher the data scale from different sensors and larger fields require more data storage requirements at the cloud and wireless communication gateway end.** The vice-versa is also true i.e. the data scalability depends upon the data storage requirements.

Table 4.2: Continued

Data storage-Type of Precision application	**P5:** “They just have everything in one box, and we provide them the MDM NWD watchdog technology through which we control the data. We **flash the images and for example if there is any breakdown in any situation we all have the backup stored data for it.** So that is something that is actually in development and I'm pretty sure that was gonna be the trying to do really resonates with what it's going to be in future.”	0.33 (Weak agreement)	**Data storage depends upon the type of Precision agriculture application.** The participants highlighted that for **monitoring row crop diseases** application the data from remote sensing, soil moisture and weather sensors can be transferred and stored overtime on **cloud-storage** providing much flexibility and **data interoperability from other open-data sources** for instance topography and soil geographic data.
Data Storage-Power consumption	**P4:** “Here's the **rest API** that you can pull the data in from so we can't quantify what the **power consumption** is for that. But then you have it on the plant side. Sometimes you might have sensors like the from the Farm beats platform where you could **determine how often you want this data. So, then that determines the power consumption that's going to be drawing.** And so that that's to give like different perspectives on sometimes you might not know how it's affecting the power consumptions. And sometimes you can see immediately that the battery level is one of the sensors that you were looking at and how the **power is being drained.”** **P9:** “I think the reality is that you know **big data and these types of processing ideas are going to make lots of cheap sensors.** Then maybe you don't know they're not scientific if you will, and **they don't update every second.** But there are lots of them a lot more valuable than one or two really fancy ones or you know **that meaning that oftentimes the cheap ones are also lower power.”**	1 (Excellent agreement)	**Data storage doesn’t depend upon the power consumption** requirements. Power consumption **depends upon the data latency requirements** i.e., data transfer rate as highlighted by participants.

Table 4.2: Continued

Power consumption-Data latency	**P3: “LoRAWAN** maybe more specific would be appropriate for like one of these, you know, **hundreds or thousands of sensors spread out over a huge area.** You know and Something like that would typically be, you know, power or battery, small battery or energy harvested kind of thing. The sensors, probably by nature, not a very fast update rate, or don't measure very often. And so, it Maps to that technology well, but there are a lot of other things you know or LoRA won't solve the problem in the space of AG One would be just, you know, **machine automation**. You know, like you'll never be able to have a **cloud connected machine that's maybe utilizing the cloud's ability to do real time computations** and have that connected through LoRA like this is probably just will never work for latency reasons.” **P5:** “LoRA gateways consume huge amounts of power so that their clients don't have to. You know. I mean, it's a balance. You can only get so much **data latency for a certain amount of power.”**	0.67 (Good Agreement)	**Data latency** depends upon the power consumption requirements as lower the latency requirements from sensors and wireless communication technologies higher the power consumption. **LoRA is a low power and higher latency** wireless communication technology protocol. The 3G/4G/5G and wireless **WIFI have more power consumption as they have low latencies-high data transfer rate and are used for autonomous applications.** Bluetooth wireless **BLE is a low power- low latency option for shorter communication range precision applications such as for RFID, GPS** and other short communication range sensor precision applications.
Typeof Precision Agriculture application - Cost	**P11:** “If you have **smart fertigation or real time like pH and electrical conductivity control,** you are just wasting money if you are doing that process on the cloud and you will be vulnerable to lack of Internet and also processing that data you're using.” **P8:** “If you get, you know that data all the time and then you know if you want to record with Iso- Blue. If you want your real data at the end of the year, you know you don't need that. By the 2nd, get that at the end of the year.”	0.75 (Excellent agreement)	**Type of precision agriculture application** depends upon the **cost requirements.** The participants reported that for monitoring row crop disease applications where data latency requirements are higher the data can be transferred to cloud storage over-time with lower bandwidth requirements and costs associated as compared to **low latency autonomous applications.**

Table 4.2: Continued

Type of Precision Agriculture Application- Data scalability	**P12: "Disease detection and management** or other things on the farm, nutrients etc comes from different sources. You might have some that would come from an egg input provider that would be doing **custom applications of pesticides or fertilizers.** There might be some coming from the **farm machinery** or come from the farmers perspective or a consultant. Or you know if you're if you're ordering **aerial imagery,** there would be that source and other." **P9:** "The **biophysical model** again right there, it might be important to have **multi-dimensional data over time to just have a richer model** to give you a very intricate observation. So, so I think depending on whether it's an autonomous application or it's a by **physical application and autonomous, a lot of data will** be good because you can take advantage of offline training."	0.67 (Good agreement)	**Type of precision agriculture application** depends upon the **data latency requirements as autonomous applications** have low latencies in milli-seconds or seconds especially **Farm machinery navigation systems using GPS and accelerometer sensors.** The smart irrigation and smart fertilization where the data from soil moisture, Ph and Nitrate sensors have data latencies requirements in **minutes or hours** as participants reported. The monitoring applications specifically for row crop diseases where days and weeks might be the data latency requirements.
Type of Sensor - Data storage	**P10: "Autonomous areas don't** really care about data that happened previously and you're **not really going to need to store historical data.** OK, except it with the exception of the monitoring applications for that autonomous. Application so I don't. I don't imagine there being a very **high data storage requirement."**	0.33 (Week agreement)	**Data storage** requirements depend upon the type of sensors. **Remote sensing sensors store and transfer large amounts of image sensing data to the cloud overtime.** However, for the **autonomous applications sensors** such as accelerometers and GPS sensors **historical data storage doesn't value much.** The participants also reported that the **variable that sensors are measuring if changing constantly requires sending and storing data consistently over time.**

Table 4.2: Continued

Type of Sensor - Type of Wireless communication Technology	**P12:** “Overkill to be sampling 8 every second so you can't save a lot and probably this is one of the biggest advantages of **LoRa. You can cover a big range and send data at a very low rate.** Yeah, instead of like, depending on a cell network modem never planned for just **measuring a slowly changing variable like temperature so.** **P13:** “As long as you **don't need image sensors, then the bandwidth requirements are negligible.** Just to give you a context. So, in our system where a single soul chip tag can connect to six simultaneous sensors we're sending something **like 50, 50 bytes, 50 bytes every five minutes.”**	0.67 (Good agreement)	**Type of wireless communication technology** depends on the type of sensors integrated. The participants reported that Autonomous applications such as **Smart Irrigation, Smart Fertilization and Farm machinery navigation have lower data latency requirements** where LoRA has a drawback of higher latency more suitable for integrating **environment, soil and Ph nitrate sensors where data latency requirements are higher as compared to Autonomous applications.**
Type of sensor - Cost	**P11:** “You have to go out there and take subsamples and that isn't near detailed enough to address the variability that's in the field. And so to me, like the big game changer that we really need is some kind of **a low cost accurate phosphorus potassium soil Ph type of a sensor.** And that, to me would revolutionize crop production more than anything.”	0.67 (Good Agreement)	Type of sensor depends on cost. **Remote sensing sensors collecting satellite data are costlier as compared to weather, soil moisture, Ph and nitrate sensors.** GPS, accelerometer.
Type of Sensor-Data Latency	**P10:** “If you're concerned about **latency** you might want to do **more of the processing on the device or on the edge or in the cloud** depending on the latency requirements of the process.” **P14:** “If your **variable doesn't change too often** then it's overkill to be sampling 8 every second so you can't save a lot and probably this is one of the biggest advantages of LoRa, So, you don't. You can **cover a big range and send a very low rate.”**	0.67 (Good agreement)	**Data latency depends upon the type of variable measured through sensors** and type of precision agriculture application. The participants reported that for smart irrigation and smart fertilization the data from soil moisture, Ph, nitrate and weather sensors **might have latency requirements in minutes or in hours.** However, GPS, accelerometer & remote sensing sensors have lower data latencies.

Table 4.2: Continued

Type of sensor-Data scalability	**P16:** “Something on the **leaves of crops,** then you would use **satellite aerial or drone typically,** and so, I mean these are sensors or **few in number,** but they're collecting a **lot of data over a wide area.”** **P14: “**So, if you're talking, you know a piece of autonomous farm equipment, Generally, would think of the data. At least of the data speed needs, there are going to be significantly higher. Most that's focused around safety, right? **Anything that involves safety typically requires high data rates and often has redundancies.”** **P12:** But like redundancies, you mean we need to **then process the data a lot**. Basically, have the implementation of control applications right. Alright, but more by redundancy I was so in talking like a vehicle scenario. You have, you know, a lot of times they are. You know they'll **have two sensors to do the job of. One for fail safe reasons,** so that's kind of where I was thinking along those lines. Compared to, you know, for in some sort of an agronomic sensing scenario,	0.67 (Good Agreement)	**Data scalability** depends upon the type of sensors. **Remote sensing** and drones can store and transfer **large amounts of image, visuals & navigation point data** from large area fields. However, for **weather, soil, Ph & Nitrate sensors** the large-scale applications will involve **more of these sensors.**

Table 4.2: Continued

Type of sensor-Data processing	**P11:** "I could call it like **multi sensor fusion** but at the same time you want to provide a usable API right so that people can understand at the front end the results may be properly visualized from the different sources and they might be **some sensor sources that are resulting in noisier data than the others.** So, you might want to normalize. With respect to that, and there are other ways of doing dimensionality reduction, right? So, if you see noisier data, **you can do more dimensionality reduction or noise removal for that, or outlier removal** for that versus the others that are clean or so. So that is one way of doing **differential analytix**. The other is related to latency, so if you're concerned about latency you might want to do more of the processing on the device or on the edge or in the cloud depending on the latency requirements."	0.33 (Weak agreement)	**Data processing** at cloud storage or at gateway or edge depends upon **sensor type as remote sensing, GPS and autonomous application sensor as reported by participants need much higher data processing at communication gateway or cloud** for driving the vehicles and generating prescription maps for row-crop diseases.
Type of Sensor power monitoring	**P15:** "I mean you can have color cameras, multi spectral camera, hyperspectral cameras, so these are the sensors that are normally you choose for. For **monitoring view crop diseases** in drops or even or even in any other crops that you would like to." **P14:** "So, the sensor could be on an aerial drone or it could be deployed in the soil. So, depending on or it can be deployed in their farm machinery. So just another way to classify depending on what we're trying to measure. Or it could be satellite sensors where you want to install a camera. For instance, **for disease monitoring or. Of, course if is not critical there, but there there's certainly higher bandwidth requirements."**	0.67 (Good agreement)	Monitoring diseases applications where **higher latency and bandwidth requirements** are there **the power consumption from the sensors might be less** as compared to **autonomous applications where latency requirements are lower.**

Table 4.2: Continued

Sensors Power autonomous	**P15:** “If you have a **sensor that's connected to an alternator in a battery on a vehicle.** Well, that's sort of the same category like you don't have to worry about power consumption of a sensor since the ones that you only **have to worry about power consumption** are those that are not mounted to an engine of some kind.”	0.67 (Good Agreement)	**Accelerometer** sensors connected to the **machinery or autonomous vehicle are battery powered and power efficient** as compared to the one’s not powered by internal engine vehicle batteries.
Type of sensor-Communication range	**P16:** “For instance, for the disease monitoring or of course if you have a **drone or some other moving vehicles that you want to photograph. These latency is not critical here, but there's certainly higher bandwidth requirements.** The area or receipt latency as being important. It depends on where the intelligence is. What I mean by that is if you are trying to irrigate automatically and say OK, I want to deliver this volume of water to the field.”	1 (Excellent agreement)	Monitoring precision applications have **higher latency** requirements having **higher bandwidth requirements for wider coverages** therefore the type of sensors used in monitoring applications are compatible with higher latency and wider communication range bandwidths.

Table 4.2: Continued

Type of Wireless Communication-Power consumption	**P14:** But for **power** we did a comparison for some of the different **wireless technologies**. I know this from the work we have done that mention this paper we were interested in the power consumption for data transfer and our goal was to decrease the data transfer for it’s obviously much **lower.** Especially **Bluetooth low energy,** right? So, 85.8% for LoRA it is 99.9% to LoRA and SigFox. So, I think just to map to a **higher granularity,** BLE is quite a bit lower, so 85 versus 6 box and low RES 99.9. So, you may have to consider that if you're thinking of data transfer using these different wireless technologies.” **P17: BLE is low power on the client side because the server side became significantly higher power.** It doesn't matter how you do it, but you can **control through modulation.** Teams where the power is in through protocols, you know so But it's likely one of the better on the client side, but overall, it may not be better than something else you know.” **P18:** “The **latency** requirements and the **power consumption.** So, we actually have found that if the **latency requirements are low** and you basically want to consume the power, and that's where we did this comparison **between the different wireless technologies** that **LoRA is much more power consuming** than **Bluetooth.** Depending on what **networking modality you will have and the** battery requirements **of that sensor,** you might want to kind of bound the amount of data transfer that is happening from the sensor to the gateway.”	0.67 (Good agreement)	**Type of wireless communication technology** depends upon **the power consumption requirements as lower the latency requirements** of the precision application such as autonomous more is the throughput rate and **higher the power consumption**.

Table 4.2: Continued

Type of wireless communication technology- Data Latency	**P16:** "Something like **LoRa-WAN** maybe more specific would be appropriate for like one of these, you know, hundreds or thousands of sensors spread out over a huge area. You know and Something like that would typically be, you know, power or battery, small battery or energy harvested kind of thing. The **sensors, probably by nature, not a very fast update rate, or don't measure very often."** **P18:** "So, **depending on the size of the data rate you want the bandwidth spreading factor.** You basically see what is your so they'll be an automated thing. Of course, if there is more autonomous data but that you have these **autonomous networking decisions** where is very you basically essentially have an API where you have the software defined decision engine to decide on which networking modality is helpful for that specific application." **P16: "The Iso- blue data** were sending that over cellular. The need I guess the need for that to be the **latency** needed. That you would if there's any like real big requirement then of needing the data right away. The only thing I can think of is knowing like we were talking about using it for **grain cart** to keep track of how much grains in each combine as they're going through the field and, but I could see you know **local Wi-Fi.** And so, using going over cellular or some other connection, you know **throughput for that want to be that high."**	0.13 (Weak agreement)	**The type of wireless communication technology** depends upon **the data latency** requirements of Precision application. The participants highlighted that **LoRA** is suitable for low power consumption and very long coverage where data latency requirements are higher such as monitoring applications where large image remote sensing, soil moisture and weather data can be transferred overtime. For autonomous precision applications where data latency requirements are higher LoRA is not suitable as **throughput is lower and 4G-5G will work better however cost goes up.**

Table 4.2: Continued

Type of Wireless communication technology- Data storage	“So, I think depending on whether it's an autonomous application or it's a by-physical application. **For autonomous, a lot of data will be good because you can take advantage of offline training and having a model that is updated once in a while.** Not necessarily always updating online.”	0.33 (Weak agreement)	**Type of wireless communication technology** depends upon data storage requirements. The participants reported that the biophysical model might have **multi-dimensional data to have an accurate model updated overtime.** However, the autonomous applications such as smart irrigation and smart fertilization having self-intelligent systems require real-time data processing for sending alerts require more data processing involving edge-computing at wireless communication end, so data storage requirements are less.
Type of Wireless communication technology-Cost	The coverage using **wireless technologies and for soil sensors LoRA will be great.** For typical applications, **Wi-Fi will be cheaper.** It's like it can support **higher throughput; cellular** is very promising, but it can **cost a lot.”** For example, the company A web **services will cost a lot,** so in that case it's better to use a microcontroller or appeal, see. That will take care of **analyzing like in real time.** Actuator two to turn on to, let's fertilizer applied. It also serves the **purpose of working as a backup if you don't have Internet,** you are fine. The PLC will work if you want to keep track of the pH and electrical connectivity, you can do that quickly.”	0.13 (Weak agreement)	**Type of wireless communication technology** depends on the type of sensors integrated. The participants reported that Autonomous applications such as Smart Irrigation, Smart Fertilization and Farm machinery navigation **have lower data latency** requirements where LoRA has a drawback of **higher latency** more suitable for integrating environment, soil and Ph nitrate sensors where data latency requirements are higher as compared to **Autonomous applications.**

Table 4.2: Continued

Types of Sensor-Data Quality	**P18:** "So there is a very good application of lots of those kinds of sensors, which means a lot of 'em that are **cheap and no one piece of data is that good**. But if I compare now to yesterday and the day before, I get a good trend of something that's happening. But there's a different class of sensor that if you're going to use a sensor essentially to **drive a biophysical model. Essentially calibrate that model from time to time.** Then you don't just wanna know that well. Yes, the soil is whether it must have rained there, you might need to know. It rained and now how deep is the? How deep did the water flow into the soil? And so that takes sort of a **different class of sensor, but you wouldn't have it all over the field. You might only have one or two of them, but you need really accurate data to drive models, and so I think there is a balance between the two."**	0.33 (Weak agreement) New relationship	**Data quality** from the sensors depends upon the **type, scale, and calibration of sensors.** Data quality might depend on the scale of sensors deployed, calibration and type of sensors used to measure biophysical variables.

The table above is developed using NVivo for content analysis and highlights the descriptive analysis of the expertise participants' responses in quotes from the focused group interviews with nodes developed from the content analysis. Nodes (variable relationship) column describes the relationship between decision variables coded from the content analysis with respective kappa values.

The relationship nodes identified from the content analysis are described below. An Interpretive Structural Modeling (ISM) methodology was applied to develop these relationships among the variables.

4.1.3 Decision Variables for Action Research Deployments

The descriptive content analysis of the focused group interviews is used to define the decision variables.

Table 4.3: Decision variables for Deployment at ACRE

Variable (Node)	**Definition (Content Analysis- Focused group interviews)**
C1- Cost (CT)	Fixed cost (Sensor cost, Communication gateway technology cost). Variable cost (Sensor batteries cost, Power consumption cost, Cloud storage subscription cost)
C2- Types of Sensors (TS)	Monitoring row crop diseases (Weather sensors (Temperature, Humidity, Light, Pressure, Soil Moisture), Remote Sensing (Drones, GPS), LIDAR image sensors), Smart Fertilization (Ph, Nitrate soil sensors), Smart Irrigation (Soil moisture, Ph level), Farm machinery autonomous operations (GPS, accelerometers, proximity, fuel level, sound).
C3- Type of Wireless Communication technologies (TWC)	3G/4G/5G**,** LoRaWAN, Sigfox, TVWS (Long communication range > 5miles to 10 miles), Mid-range (<1 mile) Zigbee, Wi-Fi, Short range (10-1000 m), Bluetooth (BLE), GPRS.

Table 4.3: Continued

C4- Type of Precision Agriculture application (TPA)	Monitoring applications (Row crop diseases), Autonomous applications (Smart Irrigation, Smart Fertilization, Farm Machinery navigation autonomous operations.
C5- Data Storage (DS)	Data storage platforms i.e. (Wireless communication gateway end), cloud (User-end- application interface).
C6- Data Scalability (DSC)	The scale or amount of data transferred for storage and processing from different types(number) of sensors to edge (communication gateway-end) or cloud (User-end application interface) for developing precision agriculture applications.
C7- Data Latency (DL)	refers to the data transfer rate (bits/secs, bytes/secs, kbps, mbps) requirements defined for sensors and wireless communication technologies integrated with sensors for transferring data.
C8-Communication Range (CR)	defined as the communication distance between the sensor node (the device integrated with different types of sensors) and wireless communication gateway technology. The Signal to Noise ratio (SNR) and Received Signal Strength Index (RSSI) are the metrics used in this research study for the empirical analysis of signal strength with a communication range.
C9- Data processing (DP)	defined as the amount of data (bits/secs, bytes/secs, kbps, mbps) processed by the communication gateway technology and cloud storage end.
C10- Power consumption (PC)	defined as power consumption by sensors, wireless communications technology integrated with sensors along with backhaul networks (Wi-Fi, GPRS- 3G/4G/5G). The operating battery voltage for sensor nodes having different types of sensors integrated is the indicator for power consumption used in the empirical analysis for this research.
C11- Data interoperability (DI)	defined as the ability of cloud storage (user-end application interface) to store and process data from different sources (different types of sensors, wireless communication mobile gateway edge, remote sensing, other open-source data) and able to communicate well with heterogeneous sensors and farm machinery for data transfer.

4.2 Interpretive Structural Modeling (ISM) analysis

The Interpretive Structural Modeling (ISM) analysis technique was used for defining the contextual relationships and developing the model among the decision variables (see section 4.1). The ISM process started from developing a contextual matrix highlighting the relationship among variables, converting the contextual relationships in defined symbols with respective scores, checked and validated by the three raters for inconsistencies matrix developed (Malone, D. W. 1975, Govindan et al. 2015, Agrawal, A. 2020).

4.2.1 Contextual relationship matrix

The alphabetic symbols used in the matrix below follows the notations:

- V=1 if i (row variables) is related to j (column variables) only but not vice-versa (j is not related to i)
- A=0 if j is related to i only but not vice-versa (i is not related to j)
- X=1 for both direction relations from variable i to j and vice-versa
- O=0 if the relation between the variables does not appear valid.

The contextual matrix highlights the pairwise relationships between variables. These pairwise relationships were converted into notations in the self -interaction matrix in the following section.

Contextual Relationship Matrix (i rows, j columns)	C1 (CT)	C2 (TS)	C3 (TWC)	C4 (TPA)	C5 (DS)	C6 (DSC)	C7 (DL)	C8 (CR)	C9 (DP)	C10 (PC)	C11 (DI)
C1 (CT)	**-**	**V** (Remote sensing sensors collecting large amounts of imagery satellite data are costlier as compared to weather, soil moisture, Ph and nitrate sensors)	**V** (Type of Wireless communication technology depends upon the cost as low latency and more scale of different types of sensors with higher processing increases the power consumption cost)	**V** (Low data latency and high data storage increases the cost of development on the cloud storage)	**V** (Data storage requirements depend upon the cost. Increasing the cloud storage subscription cost)	**V** (Data scalability depends upon the cost as it increases the sensors, data storage & processing costs)	**V** (Cost depends upon the data latency requirements as the participants reported lower data latency for autonomous applications require more power consumption for high data transfer and processing)	**X** (Communication range between sensors and wireless communication technology depends upon the cost requirements as broader the range for same data transfer requirements more power consumption)	**V** (Data processing depends upon the cost requirements as higher the processing more is the power consumption)	**V** (Variable Cost depends upon power consumption by sensors and communication gateway)	**V**(Cost of cloud storage subscription depends upon the data interoperability between different data storages)
C2 (TS)	**A**	-	**X** (LoRA long range low power, lower latency (high data transfer rate). Autonomous application sensors (GPS, accelerometer, audio) low latency-3G/Wifi/BLE (Environmental, Remote sensing)-Monitoring applications-(higher latency, low data transfer rate)- LoRA, Sigfox)	**X** (Monitoring application uses remote sensing, environmental (Temp, Humidity, Light, CO_2) and soil moisture sensors)	**A** (Data storage requirements depend on type of sensors for Remote sensing sensors involving a lot of Image processing, data points storage requirements are more)	**V** (Data scalability depends upon the type of sensors as satellite aerial or drone sensors fewer in number collects large amount of data)	**V** (Data latency depends upon the type of sensors as for autonomous applications the data from GPS, Sound and accelerometer sensors have low latency requirements)	**O** (Type of sensors doesn't depends upon the communication range as they are dependent upon the type of precision application)	**A** (Data processing depends upon type of sensors as large amount of data from remote sensing, Image sensors require more processing)	**V** (Type of sensors depends upon power consumption as remote sensing and imagery sensors consume more power as compare to thermocouple, resistive soil moisture sensors)	**A** (Data interoperability depends upon the heterogeneity of different sensors and their integration with the communication gateway technology)

Fig. 4.1: Contextual Relationship Matrix

Fig 4.1: Continued

C3 (TWC)	**A**	**X**	**-**	**X** (Type of wireless communication technology depends upon type of precision application as autonomous applications require lower latency and larger data processing)	**A** (Data storage depends upon the type of precision application as autonomous application requires edge computing increasing data storage & processing at gateway end)	**A** (Data Scalability depends upon the data processing and storage limitations of wireless communication gateway technology)	**V** (Data latency depends upon the type of precision application which depends on data latency and bandwidth range requirements LoRA)	**X** (Type of wireless communication technology depends upon communication range as for shorter ranges and lower data latency requirements for moving autonomous application LoRA might not work due to higher data latencies)	**V** (Data processing depends upon the type of wireless communication gateway. Autonomous applications might require large amount of data processing & edge computing for alert systems)	**X** (Type of wireless communication technology depends upon power consumption as lower data latency and higher processing requires more power consumption as for 3G/4G/5G & Wifi as compare to LoRA)	**X** (Type of wireless communication technology depends upon data interoperability as Type of sensors used must be compatible and interoperable with type of wireless communication gateway integrated)
C4 (TPA)	**A**	**A**	**X**	**-**	**X** (Type of precision application depends upon data storage as monitoring applications might require higher data storage from imagery & remote sensing)	**X** (Type of precision application depends upon the data scale as large-scale data might be required from different type of sensors and scale of sensors deployed)	**X** (Type of precision application depends upon data latency requirements as autonomous type precision agriculture applications might require low data latency)	**X** (Type of precision application depends upon communication range as for autonomous alert applications short & mid-range communications & lower power technologies such as BLE & Zigbee.)	**X** (Data processing depends upon the type of precision application as for Monitoring applications with higher data processing at cloud storage instead of communication gateway end)	**X** (Type of precision application depends upon the power consumption requirements as lower data latency autonomous applications might require Wifi, 3G/4G/5G communication gateway consuming more power than LoRA for wider communication ranges)	**A** (Data interoperability depends on the type of precision application as the cloud storage and communication gateway technology must be interoperable and compatible between different types of sensors)

Fig 4.1: Continued

C5 (DS)	**X**	**X**	**A**	**X**	**-**	**X** (Data storage depends upon the data scale as for large amount of data from different type of sensors require larger communicate edge gateway and cloud storage space)	**V** **(**Data latency depends upon data storage as higher data latency might require more storage of data at cloud end as compared to communication gateway edge end for Monitoring applications)	**V** **(**Communication range depends upon the data storage as for short-range applications requiring autonomous alert more data processing & storage is required at the communication gateway edge end)	**V** **(**Data processing depends upon data storage as for monitoring applications more data processing might be required at the cloud-end as data latency requirements are higher)	**O** **(**Power consumption doesn't directly depends upon the data storage rather it might depend upon the data processing rate)	**X** (Data Storage depends upon data interoperability. The data from different types of sensors must synchronize with cloud storage. More variety of sensors or data sources might require more interoperable cloud storage)
C6 (DSC)	**X**	**A**	**V**	**X**	**X**	**-**	**A** **(**Data latency indirectly depends upon the data scalability as low latency type of autonomous application require more data storage and processing at communication technology gateway end)	**O** **(**Communication range doesn't depend upon data scalability and nor vice-versa. Data scalability rather depends upon type and number of sensors)	**A** **(**Data processing depends upon the data scalability as more data processing is required for large scale of data at the cloud end for Monitoring precision applications)	**A** (Power consumption depends upon the data scalability as higher data processing and low data latency requirement for autonomous applications require more power consumption at the communication gateway technology end)	**X** (Data Scalability depends on the data interoperability as more interoperable the data storage scale of data can be increased with data from different sensors)

Fig 4.1: Continued

C7 (DL)	**A**	**A**	**X**	**X**	**A**	**V**	**-**	**X** (Data Latency depends upon the communication range as for monitoring applications covering wider areas of farm LoRA might be used having higher data latency and low power consumption)	**A** (Data processing depends upon the data latency as lower the data latency requirements of an application higher the data processing)	**X** (Data Latency depends on the power consumption has lower is the data latency (high data transfer rate) higher is the power consumption by sensor nodes and communication gateway technology)	**A** (Data interoperability indirectly depends on the data latency as low data latency might impact the compatibility of wireless communication gateway for different types of sensors)
C8 (CR)	**X**	**O**	**X**	**X**	**A**	**O**	**X**	**-**	**X** (Data processing depends upon the communication range	**X** (Communication range depends on power consumption as higher the range more power consumption is there by sensors and communication gateway technology)	**O** (Data interoperability doesn't depend on communication range)
C9 (DP)	**A**	**V**	**A**	**X**	**A**	**V**	**V**	**X**	**-**	**O** (Power consumption doesn't directly depends on the data processing rather it depends on the data latency)	**O** (Data interoperability doesn't depends on the data processing rather it depends on the data storage)

Fig 4.1: Continued

C10 (PC)	**A**	**X**	**X**	**X**	**O**	**V**	**X**	**X**	**O**	**-**	**O** (Power consumption doesn't depends on the data interoperability)
C11 (DI)	**A**	**V**	**X**	**A**	**X**	**X**	**O**	**O**	**O**	**O**	**-**

4.2.2 Self-Interaction Matrix

The self-Interaction matrix was developed using the contextual relationship matrix above with symbol notation. The highlighted cells in yellow are inconsistent with results of participants from the validity check.

Self-Interaction Matrix (i row,j column)	**C1 (CT)**	**C2 (TS)**	**C3 (TWC)**	**C4 (TPA)**	**C5 (DS)**	**C6 (DSC)**	**C7 (DL)**	**C8 (CR)**	**C9 (DP)**	**C10 (PC)**	**C11 (DI)**
C1 (CT)	1	V=1	V=1	V=1	X=1	X=1	V=1	X=1	V=1	V=1	V=1
C2 (TS)	A=0	1	X=1	V=1	A=0	X=1	V=1	O=0	A=0	X=1	A=0
C3 (TWC)	A=0	X=1	1	X=1	A=0	A=0	V=1	X=1	V=1	X=1	X=1
C4 (TPA)	A=0	A=0	X=1	1	X=1	X=1	X=1	X=1	X=1	X=1	A=0
C5 (DS)	X=1	X=1	A=0	X=1	1	X=1	V=1	V=1	V=1	O=0	X=1
C6 (DSC)	X=1	A=0	V=1	X=1	X=1	1	A=0	O=0	A=0	A=0	X=1
C7 (DL)	A=0	A=0	X=1	X=1	A=0	V=1	1	X=1	A=0	X=1	A=0
C8 (CR)	X=1	O=0	X=1	X=1	A=0	O=0	X=1	1	X=1	X=1	O=0
C9 (DP)	A=0	V=1	A=0	X=1	A=0	V=1	V=1	X=1	1	O=0	O=0
C10 (PC)	A=0	X=1	X=1	X=1	O=0	V=1	X=1	X=1	O=0	1	O=0
C11 (DI)	A=0	V=1	X=1	A=0	X=1	X=1	O=0	O=0	O=0	O=0	1

Fig. 4.2: Self-Interaction Matrix

4.2.3 Reachability Matrix

A reachability matrix shown in Figure 4.3 was subsequently validated by three interview participants from focus groups. Typical practice follows that validation with at-least 3 experts, in this study participants, per the ISM literature for validating a self-interaction matrix (Malone, D. W. 1975, Govindan et al. 2015, Agrawal, A. 2020). Inconsistencies between the self-interaction matrix and reachability matrix were resolved based on 2 out of 3 same responses with typical acceptance criteria of at least 67 % consistency, and included in the final interpretive matrix (Malone, D. W. 1975, Govindan et al. 2015, Agrawal, A. 2020).

Reachability Matrix- E1, E2, E3 (i row,j column)	C1 (CT)	C2 (TS)	C3 (TWC)	C4 (TPA)	C5 (DS)	C6 (DSC)	C7 (DL)	C8 (CR)	C9 (DP)	C10 (PC)	C11 (DI)
C1 (CT)	1	V, X, V	V,X,V	V, A,V	V,XV	V,V,V	V,A,V	V,V,V	V,A,V	V,V,A	V, V,X
C2 (TS)	A,X,A	1	X,X,O	X,V,V	V,A,A	V,V,V	V,V,X	O,O,O	A,A,V	X,X,X	X,O,A
C3 (TWC)	A,A,X	X,O,X	1	X,X,X	V,A,A	X,X,X	X,X,X	X,X,V	V,O,V	X,V,X	V,O,O
C4 (TPA)	A,A,V	X,X,X	X,X,X	1	X,V,X	X,X,X	X,X,X	X,X,V	X,X,X	X,X,X	V,V,X
C5 (DS)	X,X,V	V,V,A	A,A,O	X,A,X	1	X,X,X	A,A,V	V,V,A	V,V,A	O,O,X	X,X,A
C6 (DSC)	A,V,V	A,A,V	X,X,V	X,X,X	X,X,X	1	V,A,A	O,O,A	X,A,A	A,A,A	A,X,X
C7 (DL)	A,A,V	X,A,A	X,X,O	X,X,X	A,A,V	V,V,A	1	X,X,X	A,A,A	X,X,A	A,A,V
C8 (CR)	A,A,A	O,O,O	X,X,X	X,X,V	A,A,V	O,O,V	X,X,X	1	X,X,O	X,X,O	O,O,A
C9 (DP)	A,V,A	V,V,A	A,O,A	X,X,X	A,A,V	X,V,V	V,V,V	X,X,O	1	X,V,V	O,O,X
C10 (PC)	A,A,V	X,X,X	X,A,X	X,X,X	O,O,X	V,V,V	X,X,V	X,X,O	X,A,A	1	O,O,X
C11 (DI)	A,A,X	X,O,V	A,O,O	A,A,X	X,X,V	V,X,X	V,V,A	O,O,V	O,O,X	O,O,X	1

Fig. 4.3: Reachability Matrix

4.2.4 Final Interpretive Matrix

The final interpretive matrix in Figure 4.4 was developed by removing inconsistencies from the reachability matrix and providing a score for each cell symbol notation noted in section 4.2.1. The driving power for cluster analysis was calculated by adding the column cells and the dependence power by adding up the row cells. The driving power for each variable is defined as the total number of variables influenced by a variable, For instance, the Cost (CT) variable has a driving power 11, which means it influences 11 variables. The dependence power for each variable is defined as the total number of variables that the variable is dependent upon or influenced. For instance, the Type of Precision Application (TPA) variable has a dependence power 10, which means it is dependent upon 10 other variables.

Interpretive matrix (i row,j column)	C1 (CT)	C2 (TS)	C3 (TWC)	C4 (TPA)	C5 (DS)	C6 (DSC)	C7 (DL)	C8 (CR)	C9 (DP)	C10 (PC)	C11 (DI)	Driver Power
C1 (CT)	1	V=1	V=1	V=1	V=1	V=1	V=1	V=1	V=1	V=1	V=1	11
C2 (TS)	A=0	1	X=1	V=1	A=0	V=1	V=1	O=0	A=0	X=1	A=0	6
C3 (TWC)	A=0	X=1	1	X=1	A=0	X=1	X=1	X=1	V=1	X=1	O=0	8
C4 (TPA)	A=0	X=1	X=1	1	X=1	X=1	X=1	X=1	X=1	X=1	V=1	10
C5 (DS)	X=1	V=1	A=0	X=1	1	X=1	A=0	V=1	V=1	O=0	X=1	8
C6 (DSC)	V=1	A=0	X=1	X=1	X=1	1	A=0	O=0	A=0	A=0	X=1	6
C7 (DL)	A=0	A=0	X=1	X=1	A=0	V=1	1	X=1	A=0	X=1	A=0	6
C8 (CR)	A=0	O=0	X=1	X=1	A=0	O=0	X=1	1	X=1	X=1	O=0	6
C9 (DP)	A=0	V=1	A=0	X=1	A=0	V=1	V=1	X=1	1	V=1	O=0	7
C10 (PC)	A=0	X=1	X=1	X=1	O=0	V=1	X=1	X=1	A=O	1	O=0	7
C11 (DI)	A=0	V=1	O=0	A=0	X=1	X=1	O=0	O=0	O=0	O=0	1	4
Dependence power	3	8	8	10	5	10	8	8	6	8	5	79

Fig. 4.4: Interpretive Matrix

4.3 Partitioning of Interpretive Matrix

The final interpretive matrix developed helps to partition and build a final Interpretive Structure Model. A reachability set consists of a set of variables that are influenced by a particular variable, which is defined by its driving power (Singh, M. D., & Kant, R. 2008). An antecedent set consists of variables that are dependent on a variable, which is defined by its dependence power. For instance, the Cost (CT) variable has reachability and dependencies to all the other 10 variables including itself, Whereas Data Interoperability (DI) has the least reachability and dependency i.e., to 4 variables (Type of Sensors (TS), Data Storage (DS) and Data Scalability (DSC)) including itself. The intersection set contains common variables in reachability and antecedents sets.

Table 4.4: Iteration for partitioning of Interpretive matrix

Iteration- 1

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
C1	C1, C2, C3, C4, C5, C6, C7, C8, C9, C10, C11	C1, C5, C6	C1, C5, C6	
C2	C2, C3, C4, C6, C7, C10	C1, C2, C3, C4, C5, C9, C10, C11	C2, C3,C4,C10	
C3	C2, C3, C4, C6, C7, C8, C9, C10	C1, C2, C3, C4, C6, C7, C8, C10	C2, C3, C4, C6, C7, C8, C10	
C4	C2, C3, C4, C5, C6, C7, C8, C9, C10, C11	C1, C2, C3, C4, C5, C6, C7, C8, C9, C10	C2, C3, C4, C5, C6, C7, C8, C9, C10	
C5	C1, C2, C4, C5, C6, C8, C9, C11	C1, C4, C5, C6, C11	C1, C4, C5, C6, C11	
C6	C1, C3, C4, C5, C6, C11	C1, C2, C3, C4, C5, C6, C7, C9, C10 ,C11	C1, C3, C4, C5, C6, C11	1
C7	C3, C4, C6, C7, C8, C10	C1, C2, C3, C4, C7, C8, C9, C10	C3, C4, C7, C8, C10	
C8	C3, C4, C7, C8, C9, C10	C1, C3, C4, C5, C8, C9	C3, C4, C8, C9	
C9	C2, C4, C6, C7, C8, C9, C10	C1, C3, C4, C5, C8, C9	C4, C8, C9	
C10	C2, C3, C4, C6, C7, C8, C10	C1, C2, C3, C4, C7, C8, C9, C10	C2, C3, C4, C7, C8, C10	
C11	C2, C5, C6, C11	C1, C4, C5, C6, C11	C5, C6, C11	

Table 4.4: Continued

Iteration 2

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
C1	C1, C2, C3, C4, C5, C7, C8, C9, C10, C11	C1, C5	C1, C5	
C2	C2, C3, C4, C7, C10	C1, C2, C3, C4, C5, C9, C10, C11	C2, C3,C4,C10	
C3	C2, C3, C4, C7, C8, C9, C10	C1, C2, C3, C4, C7, C8, C10	C2, C3, C4, C7, C8, C10	
C4	C2, C3, C4, C5, C7, C8, C9, C10, C11	C1, C2, C3, C4, C5, C7, C8, C9, C10	C2, C3, C4, C5, C7, C8, C9, C10	
C5	C1, C2, C4, C5, C8, C9, C11	C1, C4, C5, C11	C1, C4, C5, C11	
C7	C3, C4, C7, C8, C10	C1, C2, C3, C4, C7, C8, C9, C10	C3, C4, C7, C8, C10	2
C8	C3, C4, C7, C8, C9, C10	C1, C3, C4, C5, C8, C9	C3, C4, C8, C9	
C9	C2, C4, C7, C8, C9, C10	C1, C3, C4, C5, C8, C9	C4, C8, C9	
C10	C2, C3, C4, C7, C8, C10	C1, C2, C3, C4, C7, C8, C9, C10	C2, C3, C4, C7, C8, C10	2
C11	C2, C5, C11	C1, C4, C5, C11	C5, C11	

Table 4.4: Continued

Iteration 3

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
C1	C1, C2, C3, C4, C5, C8, C9, C11	C1, C5	C1, C5	
C2	C2, C3, C4	C1, C2, C3, C4, C5, C9, C11	C2, C3, C4	3
C3	C2, C3, C4, C8, C9,	C1, C2, C3, C4, C8,	C2, C3, C4, C8	
C4	C2, C3, C4, C5, C8, C9, C11	C1, C2, C3, C4, C5, C8, C9	C2, C3, C4, C5, C8, C9	
C5	C1, C2, C4, C5, C8, C9, C11	C1, C4, C5, C11	C1, C4, C5, C11	
C8	C3, C4, C8, C9	C1, C3, C4, C5, C8, C9	C3, C4, C8, C9	3
C9	C2, C4, C8, C9	C1, C3, C4, C5, C8, C9	C4, C8, C9	
C11	C2, C5, C11	C1, C4, C5, C11	C5, C11	

Iteration 4

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
C1	C1, C3, C4, C5, C9, C11	C1, C5	C1, C5	
C3	C3, C4, C9	C1, C3, C4	C3, C4	
C4	C3, C4, C5, C9, C11	C1, C3, C4, C5, C8, C9,	C3, C4, C5, C9	
C5	C1, C4, C5, C9, C11	C1, C4, C5, C11	C1, C4, C5, C11	
C9	C4, C9	C1, C4, C5, C9	C4, C9	4
C11	C2, C5, C11	C1, C4, C5, C11	C5, C11	

Table 4.4: Continued

Iteration 5

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
C1	C1, C3, C4, C5, C11	C1, C5	C1, C5	
C3	C3, C4	C1, C3, C4	C3, C4	5
C4	C3, C4, C5, C11	C1, C3, C4, C5, C10	C3, C4, C5	
C5	C1, C4, C5, C11	C1, C4, C5, C11	C1, C4, C5, C11	5
C11	C5, C11	C1, C4, C5, C11	C5, C11	5

Iteration 6

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
C1	C1, C4	C1	C1	
C4	C4	C1, C4	C4	6

Iteration 7

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
C1	C1	C1	C1	7

The variables have been clustered above based on their driving power and dependence power into four categories autonomous, dependent, linkage and independent variables (Malone, D. W. 1975). The objective behind the categorization of variables is to develop a cluster analysis (Singh, M. D., & Kant, R. 2008). The first cluster of autonomous variables have weak driving power and weak dependence power. The autonomous variable i.e., Data interoperability (see Figure 4.5) is weakly connected to IoT based wireless sensors network (WSN) data pipeline system through Data storage (DS) and Data Scalability (DSC) which might further impact Cost (CT) variables. The second cluster consists of dependent variables that have weak driving power and strong dependence power. Data Latency (Data transfer rate DL), Communication Range (CR), Data Scalability (DSC) and Type of Sensors (TS) and are the dependent variables with strong linkages and dependence on other variables in IoT based WSN data pipeline system. The third cluster of linkage variables have strong driving and dependence power. Power consumption (PC), Type of Precision Application (TPA), Data Processing (DP) and Type of Wireless Communications (TWC) are the linkage variables that influence the other variables. The fourth cluster of independent variables have strong driving power and weak dependence power. Cost (CT) and Data Storage (DS) are the independent variables in IoT based WSN data pipeline system used for ACRE deployment. The subsequent section describes all the clustered variables in an Interpretive Structural Model generated from the initial reachability matrix.

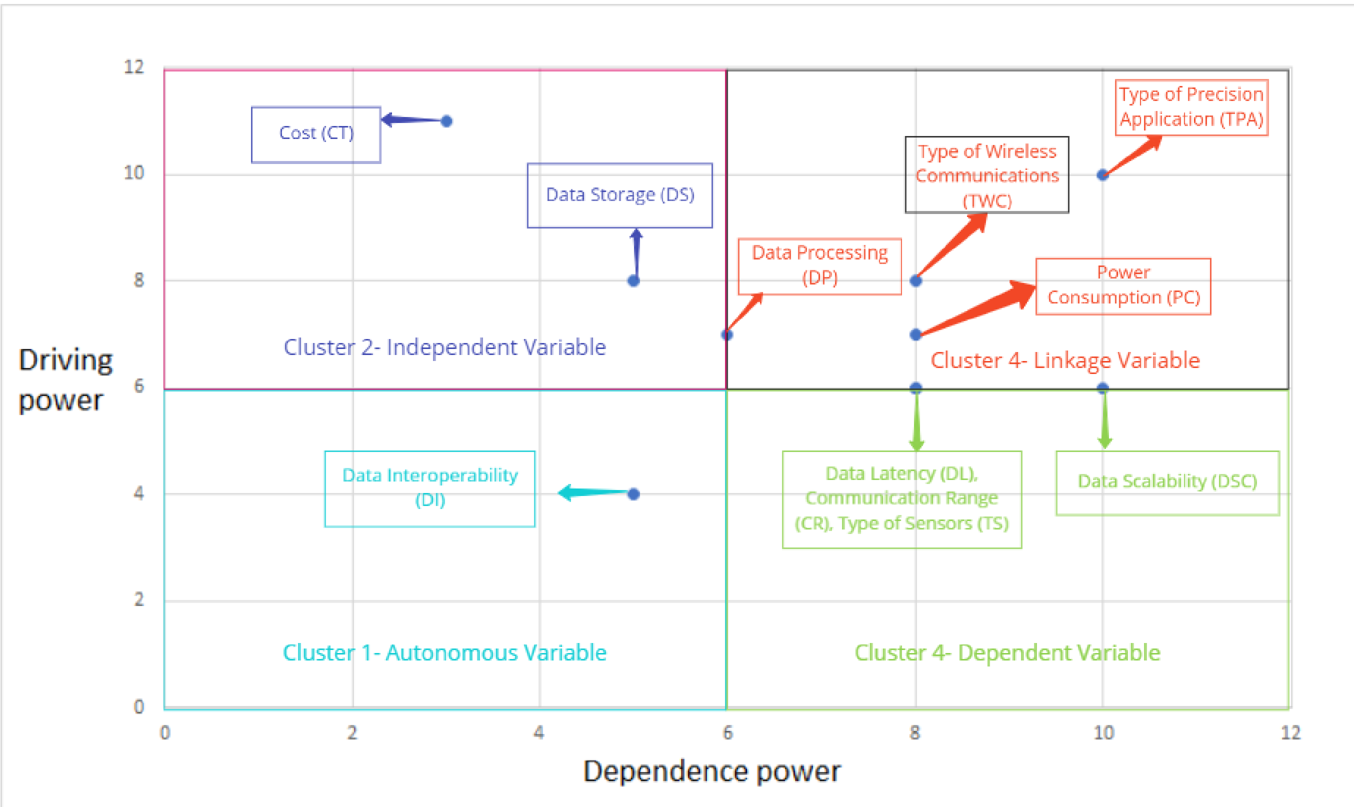


Fig. 4.5: Cluster Analysis

4.3.1 Interpretive Structural Model (ISM)

The ISM in Figure 4.6 was generated from partitioning of the initial reachability matrix (see section 4.2.1). The relationship between the decision variables i and j is presented by an arrow which points from i to j. The outward pointed arrows represent the dependency relationship whereas the inward pointed arrow represents the drivability of the decision variable. For example, the Cost (CT) variable has the maximum drivability (11) whereas Data Scalability (DSC) and Type of Precision Application (TPA) has the maximum dependency (10).

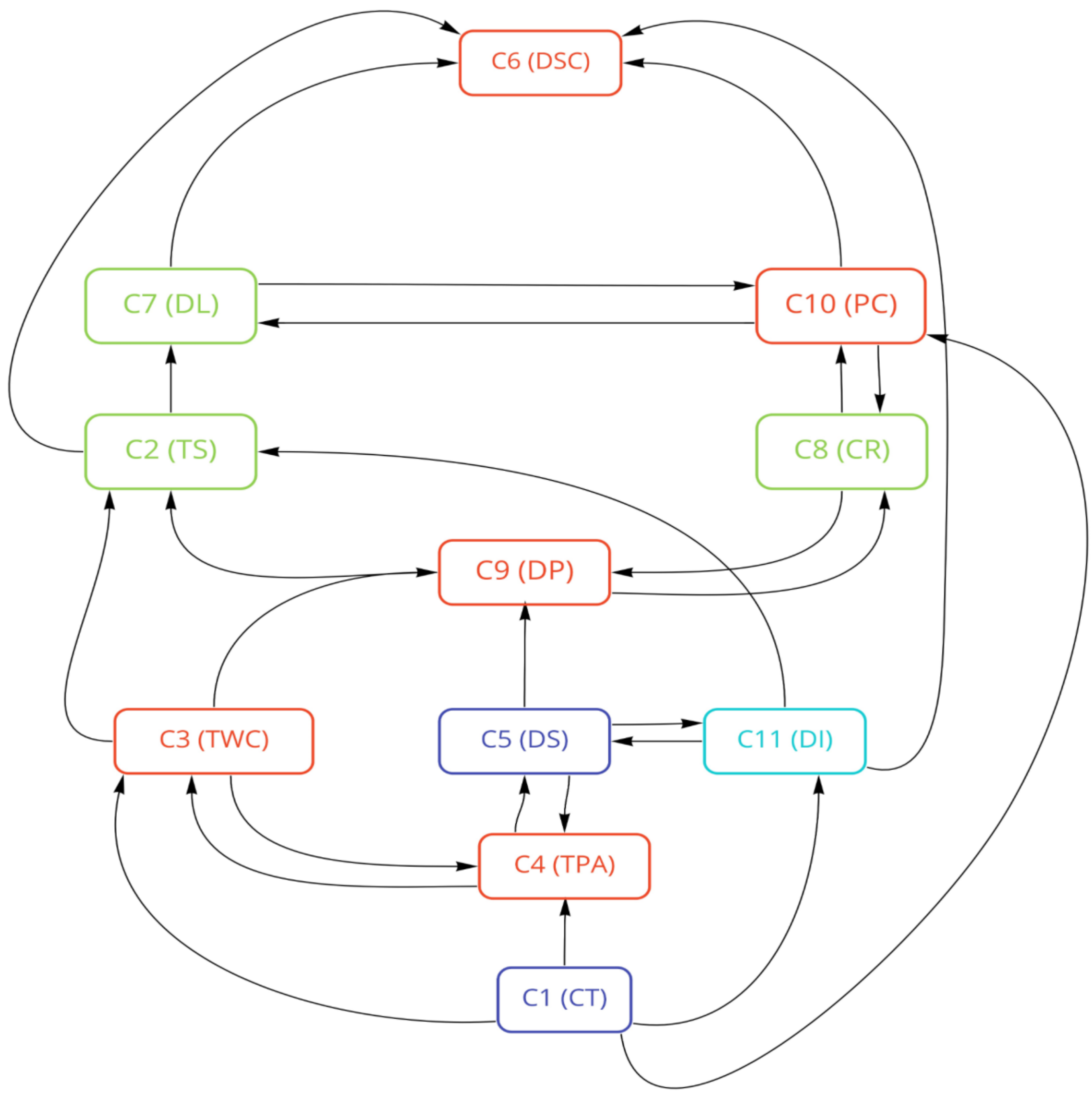


Fig. 4.6: Final ISM model highlighting relationships among the decision variables

The transitivity from the relationships were removed in the Interpretive Structural Model in Figure. 4.7. The transitive relation between the variables were removed per typical practice in the literature (Malone D. W. 1975, Singh & Kant. 2008).

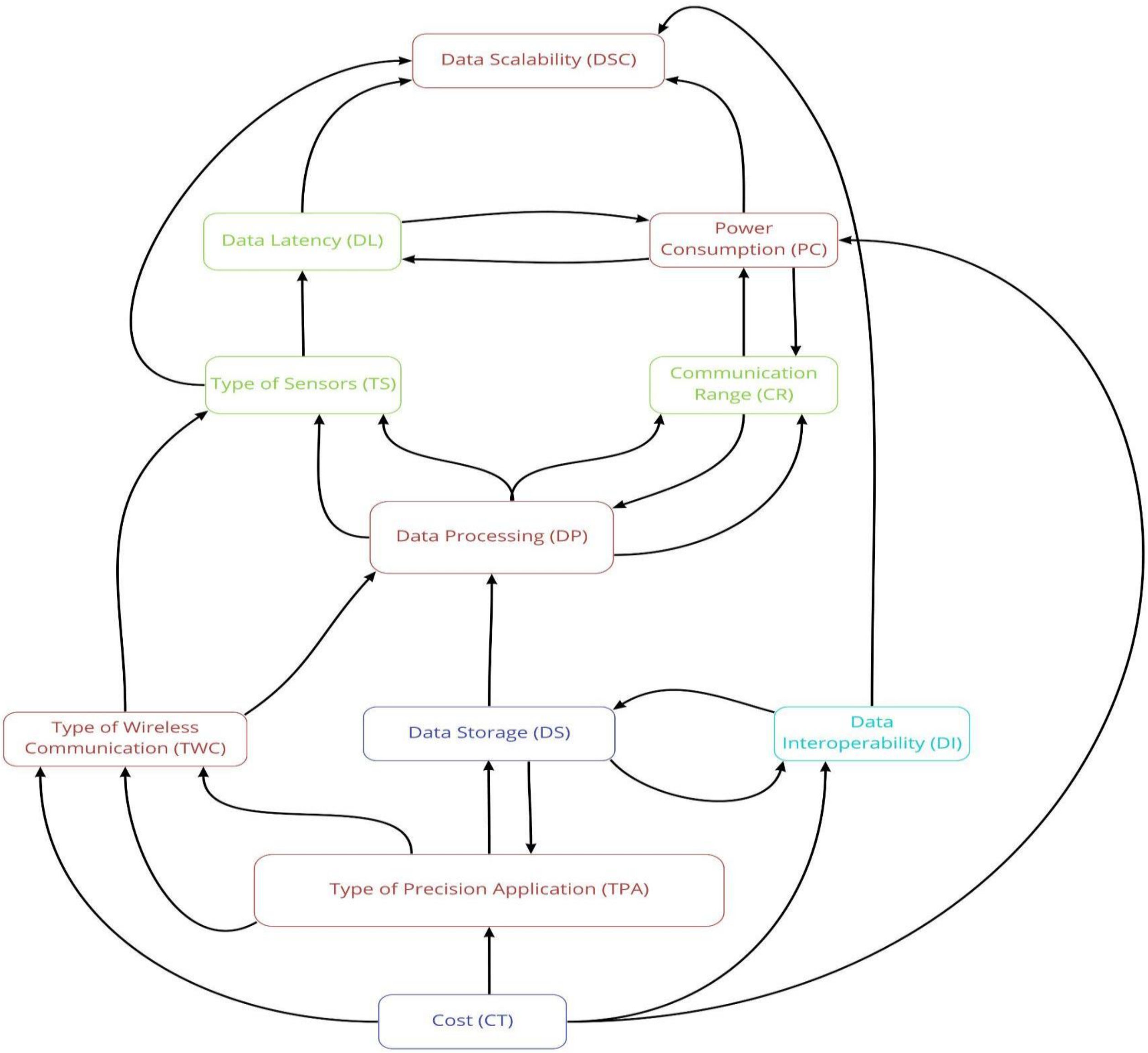


Fig. 4.7: Final ISM digraph without transitive relationships

The Interpretive Structural Model (ISM) above defines the relationship among the 11 decision variables identified from interview data and analyzed through the cluster analysis. Cost (CT), Power Consumption (PC), Data Latency (DL), Communication Range (CR), Data Scalability (DSC) and Data Storage (DS) are the critical decision variables for a Lean and Green Precision Agriculture IoT deployment. Part of the ISM model involving decision variables Cost (CT), Type of Wireless Communication (TWC), Data Storage (DS), Data Scalability (DSC), Power Consumption (PC) was used to redesign the ACRE testbed. High subscription cost related to non-open-source cloud, high sensor node battery power consumption cost, complex user-interface and non-interoperable wireless communication were the design issues related to decision variables and were redesigned for improvements following informed action research approach. The performance real time data from the redeployed IoT sensors was used to empirically validate other part of the ISM model involving decision variables Battery Voltage (BV), Data Latency (Data transfer rate), Communication Range (CR), Signal to Noise Ratio (SNR) and Received Signal Strength Index (RSSI). The correlation analysis developed between these decision variables informed sensor node battery power consumption cost and maintenance decisions during redeployment of IoT sensors.

4.4 Internet of Things (IoT) sensors deployments and comparison

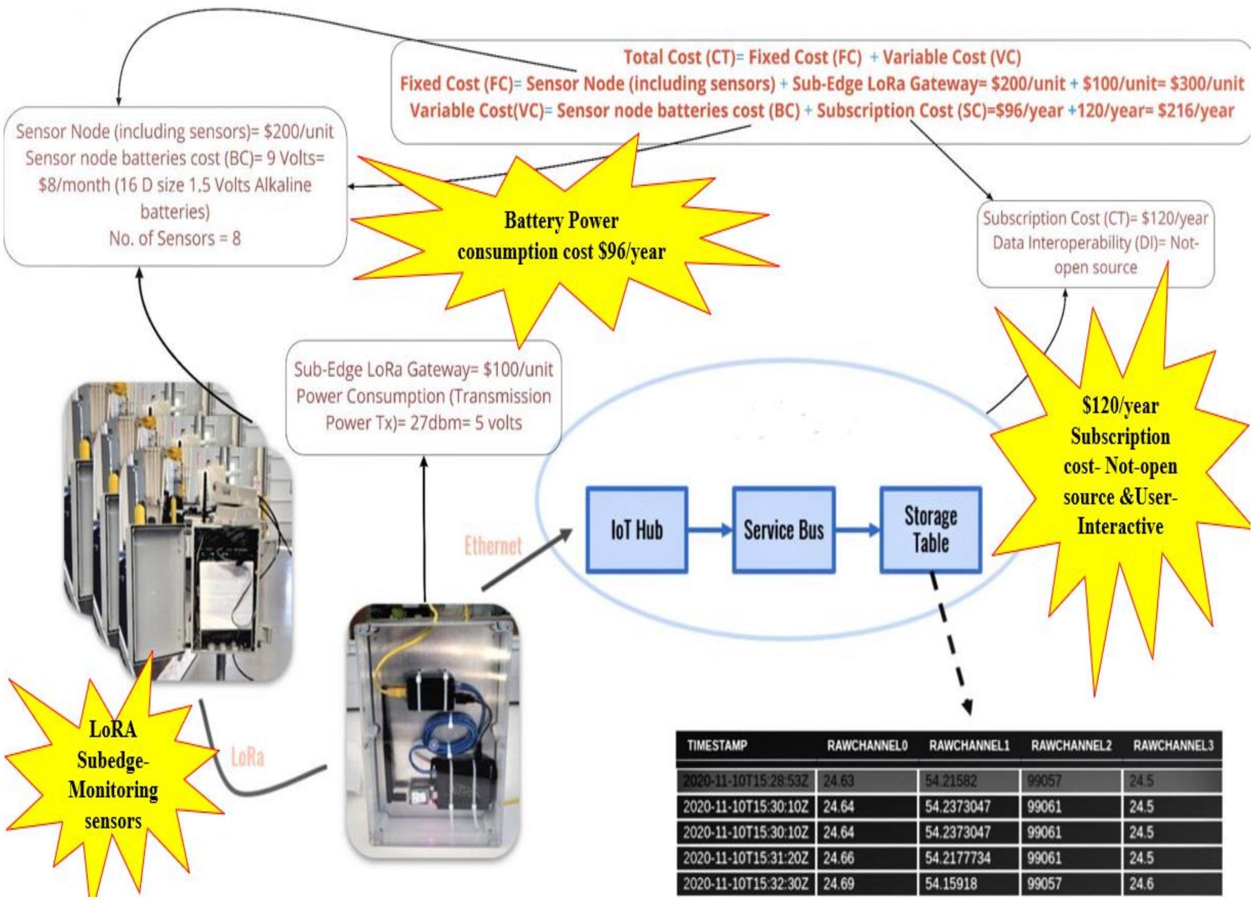
The section describes the ACRE deployments. The initial deployment (sensor node A) had issues related to high subscription cost of cloud, high sensor node battery power consumption cost, non-open-source cloud and non-interoperable wireless communication. These issues were identified through participatory action research. The ISM developed from the focused group interviews informed the design improvements for the 2nd deployment, or re-deployment (sensor node B). The comparison of action research deployments was based upon the interventions of the ACRE testbed, informed by the decision variables (see Table 4.5).

Picture 4.1: Initial deployment (sensor node A) & Redeployment (sensor node B)

The picture above shows the deployments, redesigning based upon two types of sensor nodes, that have two different Internet of Things (IoT) data pipeline designs. The comparison of the deployments is highlighted in Table 4.5. based upon testbed design improvements to make the 2nd deployment more cost efficient, energy efficient and data interoperable.

4.4.1 Initial Deployment

The ACRE deployment data pipeline is described below, highlighting the cost analysis and power consumption analysis by the researcher.



TIMESTAMP	RAWCHANNEL0	RAWCHANNEL1	RAWCHANNEL2	RAWCHANNEL3
2020-11-10T15:28:53Z	24.63	54.21582	99057	24.5
2020-11-10T15:30:10Z	24.64	54.2373047	99061	24.5
2020-11-10T15:30:10Z	24.64	54.2373047	99061	24.5
2020-11-10T15:31:20Z	24.66	54.2177734	99061	24.5
2020-11-10T15:32:30Z	24.69	54.15918	99057	24.6

Fig. 4.8: Initial Deployment of the ACRE Internet of Things (IoT) data pipeline

The first deployment before this study had the capacity of integrating 8 different types of sensors (Ambient Temperature & Humidity, Soil moisture, Light, Atmospheric pressure, CO_2, Wind speed & Rain gauge) within an IoT data pipeline. The Total Cost (CT) analysis of the data pipeline consisted of Fixed Cost (FC) and Variable Cost (VC) and is highlighted in Figure 4.8. The Fixed Cost (FC) consists of sensor node cost (including sensors) and communication gateway technology cost, which was a sub-edge LoRA (Low power wide area) gateway having power consumption of 5 volts or 27 dbm transmission power consumption. The power consumption by the initial deployment (including 8 sensors) was 9 volts with $8/month and $96/year in power consumption cost for the sensor batteries, a variable cost. The Variable Cost (VC) also consisted of cloud storage subscription costs which was $120/year. The issues related to the sensor node design, power consumption, data interoperability and high variable cost were subsequently improved with the informed action research from the content analysis of the focus group interviews.

4.4.2 Action Research Redeployment

The second deployment (sensor node B) was informed by the focus group interview data analysis, following the action research methodology. The sub-edge LoRA radio in the sensor deployment A was replaced by LoRAWAN communication gateway network of Ag-IT, which is an interoperable solution integrating different type of sensors i.e., GPS (Autonomous) & Monitoring (Temperature, Humidity, Soil Moisture & Light) sensors. The issue of data interoperability was resolved by adopting completely open-source data pipeline, consisting of a cloud Things board network for integrating multiple types of sensors and visualization of real-time data. The Things network is an open-source cloud platform was adopted by the researchers in this study to develop and deploy an open-source data pipeline to improve. This informed intervention of integrating the IoT data pipeline with an open-end cloud platform removed the subscription cost, thereby decreasing the total variable cost by 91 % from $216/year to $20/year. The power consumption by the redeployment was lowered by 60 %, with half of the capacity of the initial deployment, integrating 4 different types of sensors, compared to the 8 sensors in the initial deployment. Therefore, the power consumption cost by the sensor node batteries was reduced by 80 %, from $96/year to $20/year, lowering the capacity from 8 sensors to 4 sensors in the redeployment (sensor node B). This validates the findings from the focused group interviews describing the relationship between type & number of sensors on power consumption by sensor nodes. The relationship between Data interoperability (DI) and Cost (CT) has also been validated with the informed intervention of integrating an open-source Thing's network in the redeployment. The ACRE design improvements, with a reduction in variable cost by $204, a reduction in sensor node battery power consumption cost by 80%, an increase in interoperability of wireless communication LoRAWAN, integrating Monitoring & GPS (Autonomous) sensors, see Figure 4.9.

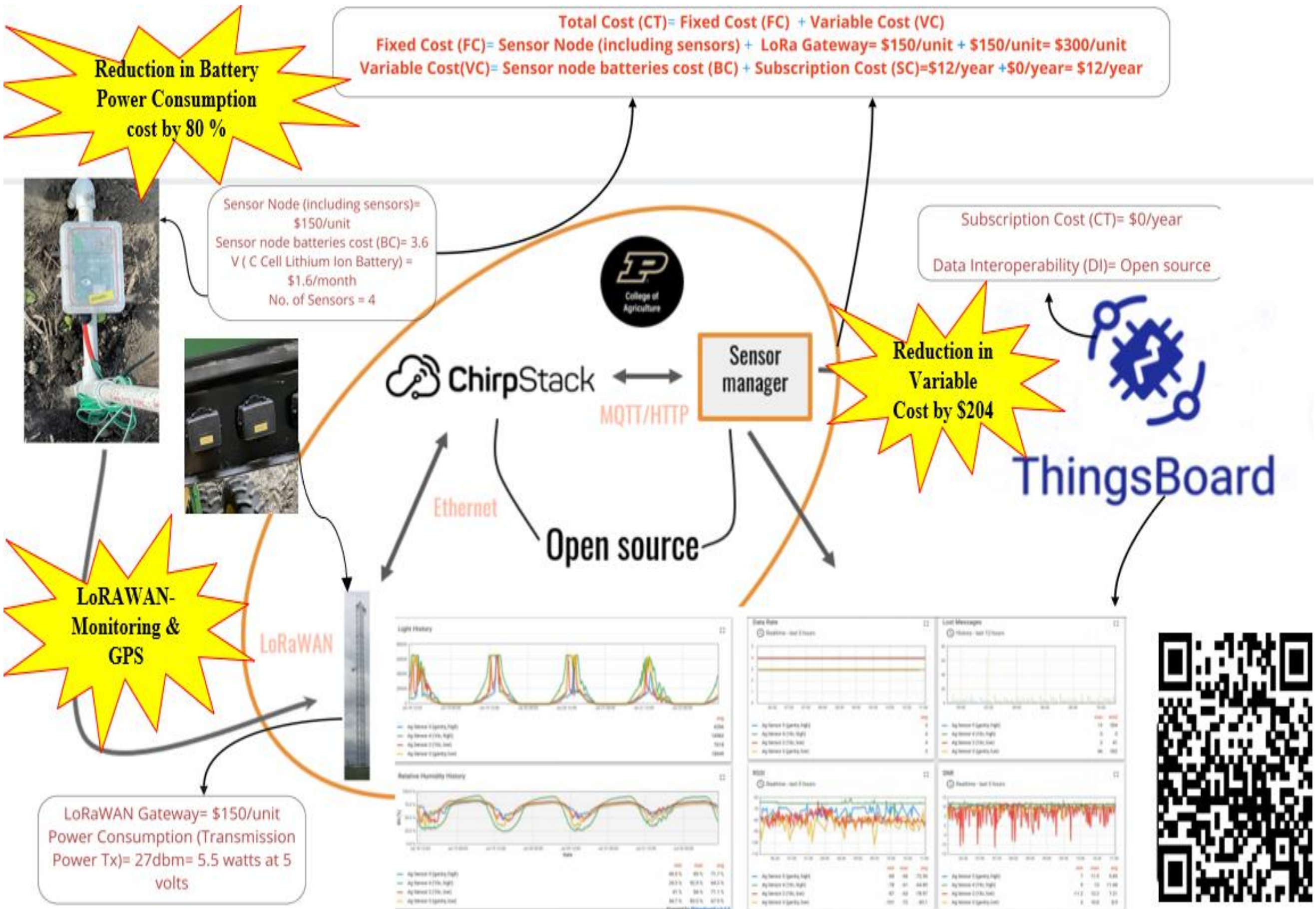


Fig. 4.9: Redeployment of the ACRE Internet of Things (IoT) data pipeline

The ACRE deployment performance comparison is described in Table 4.5. The comparison validates part of ISM, in the context of intervened actions by the researcher and subsequent findings, confirming the relationship among the variables of Cost (CT), Power Consumption (PC), Data Storage (DS), Data Scalability (DSC), Data Interoperability (DI) and Type of Wireless Communication (TWC).

Table 4.5: Comparison of Sensor nodes A & B deployments

Variable	**Sensor node A Deployment**	**Informed Action Research intervention- Focused group interview findings**	**Sensor node B Deployment**	**Comparison & Validation- ISM model**
Cost (CT)	Total Cost (CT)=Fixed Cost (FC) +Variable Cost (VC) Fixed Cost (CT)= Sensor Node (including sensors) + Sub-Edge LoRa Gateway= \$200/unit + \$100/unit= \$300/unit Variable Cost (VC)= Sensor node batteries cost (BC) + Subscription Cost (SC)=\$96/year +120/year= \$216/year	Sensor scale reduction from 8 to 4 sensors (Temperature, Humidity, Soil Moisture & Light). The power (battery) consumption cost decreased by 80% with 50% reduction in data scale per unit sensor node. Cloud subscription cost got eliminated by interoperable & open-source cloud data storage.	Total Cost (CT)= Fixed Cost (FC) + Variable Cost (VC) Fixed Cost (FC)= Sensor Node (including sensors) + LoRa Gateway= \$150/unit + \$150/unit= \$300/unit Variable Cost (VC)= Sensor node batteries cost (BC) + Subscription Cost (SC)=\$20/year +\$0/year= \$12/year	Cost (CT)-Power Consumption (PC)- Data interoperability (DI)- Data Scalability (DSC)
Power Consumption (PC)	Sensor node batteries power consumption= 9 volts (16 D size 1.5 volts Alkaline batteries). Sensor node batteries power consumption cost= \$8/month	The power(battery) consumption cost decreased by 80% with 50% reduction in data scale per unit sensor node and change in battery type from Alkaline to Lithium-Ion C cell batteries.	Sensor node batteries power consumption= 3.6 volts (C cell Lithium-Ion batteries). Sensor node batteries power consumption cost=\$1.6/month	Power consumption (PC) -Data Scalability (DSC)
Data Interoperability (DI)	The cloud storage platform used in the deployment is not open-source and interoperable for different types of sensors & other cloud storages. Moreover, there is a subscription cost of \$10/month or \$120/year associated.	The cloud storage for the application layer (Data storage, processing & visualization) is changed to an interoperable open-source user-interactive Things network.	The Things network cloud platform used in the deployment is open-source & interoperable with no-subscription cost. The data interoperability of the Things cloud storage is more as it is compatible with both monitoring (Temperature, Humidity, Soil Moisture & Light) & autonomous (GPS) sensors.	Data interoperability (DI)-Data Storage (DS)

Table 4.5 continued

Type of Wireless Communication (TWC)	Sub-Edge LoRA gateway average power consumption (Transmission Power Tx) = 27dbm=5.5 watts at 5 volts. The researchers were able to integrate 2 sensor nodes per sub-edge LoRA radio gateway.	The subedge LoRA radio used in the first deployment is replaced with LoRAWAN Gateway network with more capacity of integrating different types of sensor nodes with almost the same amount of power consumption and cost of deployment.	The LoRAWAN gateway network used in the deployment has the same power consumption (Transmission Power Tx) = 27dbm=5.5 watts at 5 volts. For the wider area LoRAWAN network sensor node integration capacity increased from 2 to 5 nodes integrated with the LoRAWAN network.	Type of Wireless Communication (TWC)- Data Scalability (DSC)
Data Storage (DS)	The cloud data storage used in the deployment is not open source which means the interoperability between different types of sensors apart from the monitoring sensors in the deployment. The autonomous sensors (GPS) are not compatible with cloud storage.	The cloud data storage platform is changed to an interoperable open-source Things network having the capacity to integrate autonomous (GPS) and monitoring sensors (Temperature, Humidity, Soil Moisture & Light) as compared to the cloud platform used in 1st deployment.	The Thingsboard network is interoperable between different types of sensors i.e both monitoring and autonomous (GPS) sensors. The researchers deployed and integrated 6 sensor nodes with the Things board having 4 monitoring and 2 GPS sensors.	Data Storage-Data Interoperability
Data Scalability (DSC)	Data Scalability depends upon the number of sensor nodes and number of sensors integrated. The first deployment is with two sensor nodes having 8 same types of monitoring sensors in each node i.e., 16 in total.	The interoperability of Thingsboard open-source cloud increases the capacity of integrating and aggregating data from different types of heterogeneous sensors i.e., both monitoring and autonomous sensors.	Data scalability increased with interoperable and open-source Things board clouds integrating 6 sensor nodes with 4 agriculture monitoring sensor nodes having 4 sensors in each node i.e., 16 monitoring sensors and 2 GPS sensors i.e., 18 in total.	Data Scalability- Data Interoperability

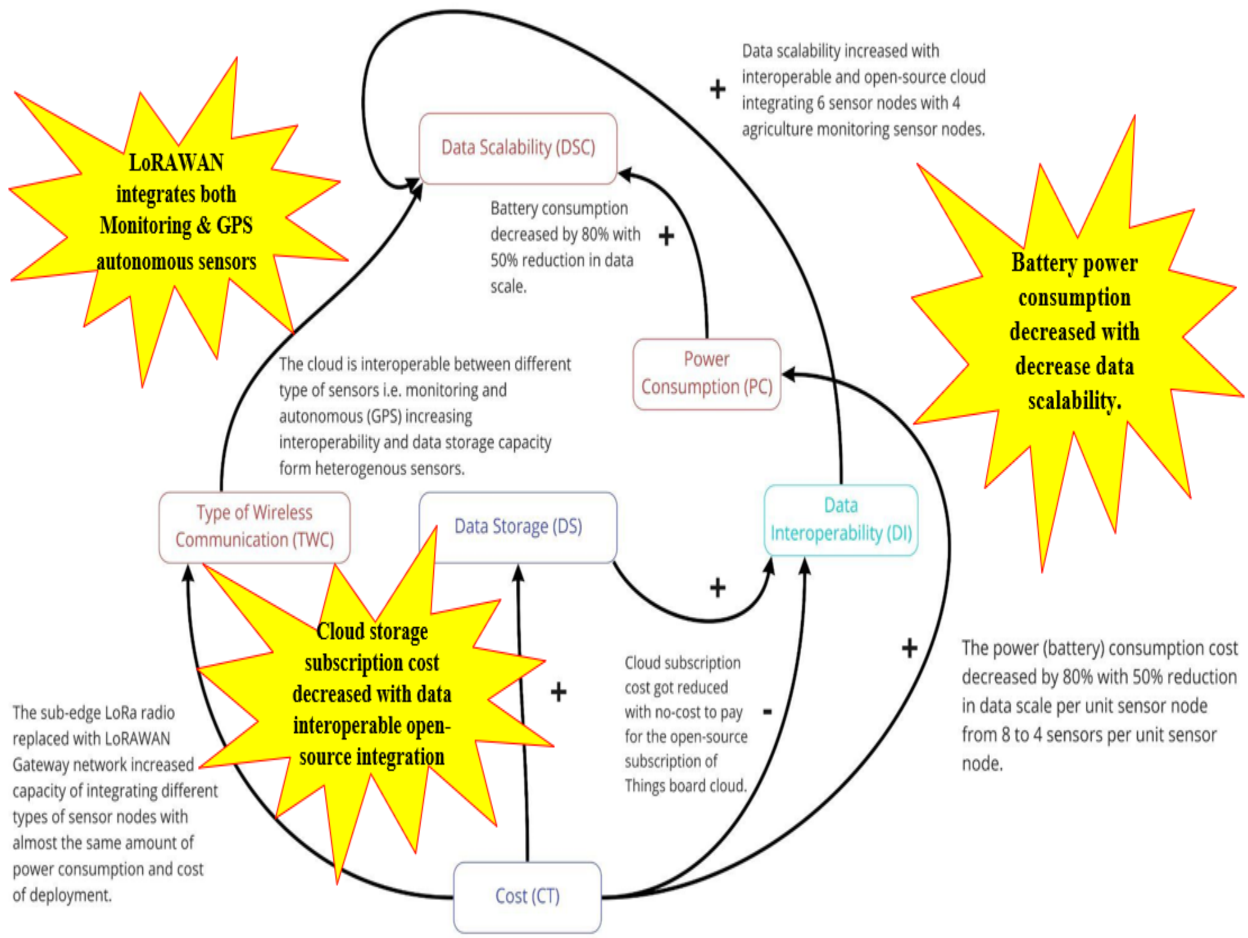


Fig. 4.10: Validation of ISM model action research deployments findings

The part of the Interpretive Structure Model (ISM) highlighted in Figure 4.10 above was informed the action research redeployments with design improvements. Cost was reduced by $204 with no subscription cost for an open-source Things Network, Sensor node battery consumption cost was reduced by 80%, the design improvements of Data-Interoperable LoRAWAN wireless communication gateway integrating both Monitoring & GPS (Autonomous sensors) in the redeployment.

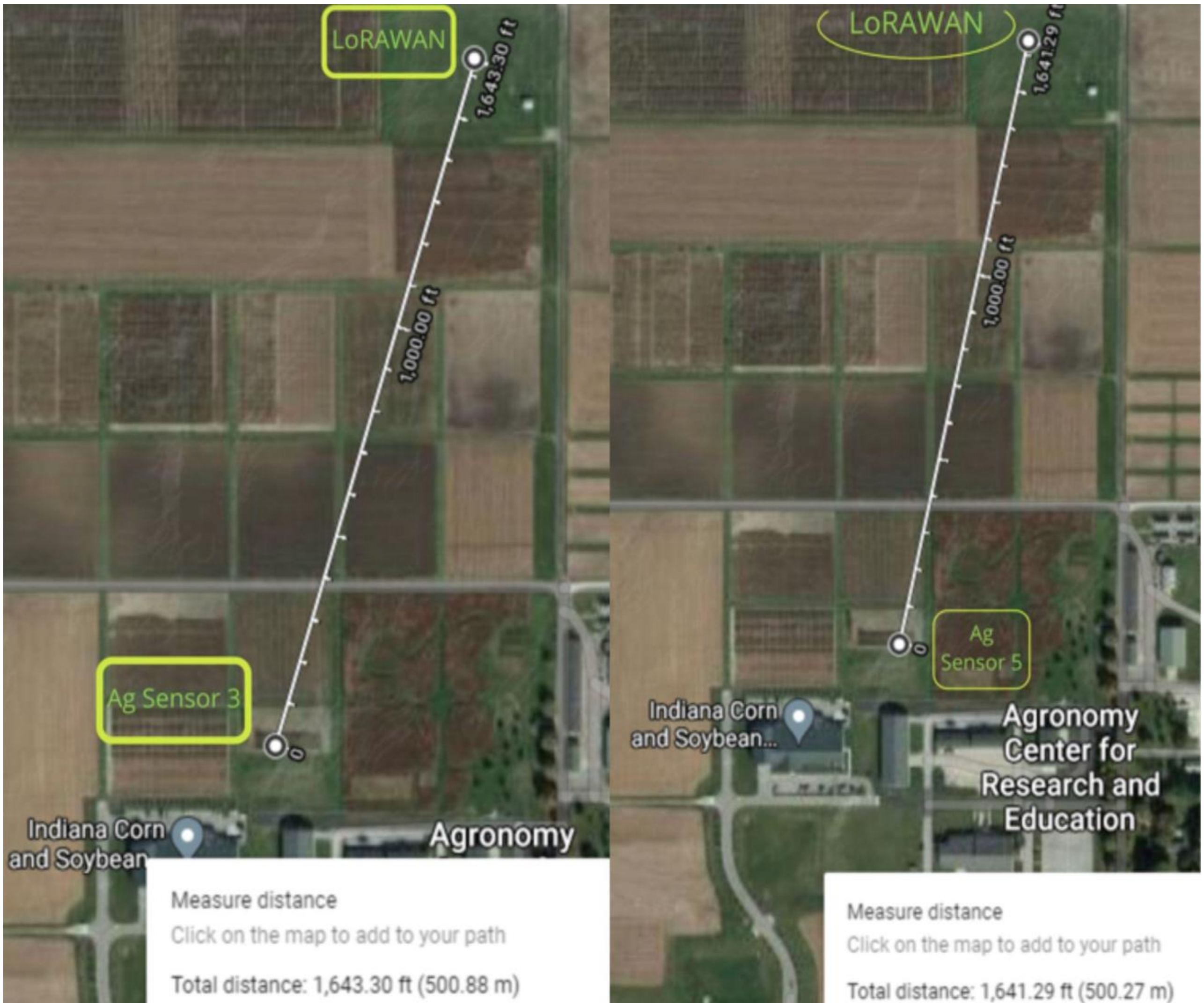
The other part of the ISM model of the correlations between (Data Latency (Data Rate (DR)), Communication Range (CR), Power Consumption (Battery Voltage (BV)), Received Signal Strength Index (RSSI) and Signal to Noise ratio (SNR)), were empirically validated through analysis and comparison of real time performance data from the IoT sensors deployed at ACRE.

4.5 Empirical Validation of ISM model- IoT sensors performance data

The empirical validation of the Interpretive Structural Model is described below, with correlation analysis conducted, using the performance data obtained (redeployed sensors 3 & 5 in corn plot and Ag Sensors 1,2,4 in soybean plot). The location and distance of the redeployed sensors from Low Power Wide Area Network (LoRAWAN) is also shown in the pictures 4.2, 4.3, 4.4, 4.5 with the orientation of redeployed sensors shown. The real time performance data was from a single day, the 1st day of growing season, and was analyzed using multiple regression. The rationale behind using 1st day of growing season data was primarily to exclude potential canopy growth effects.

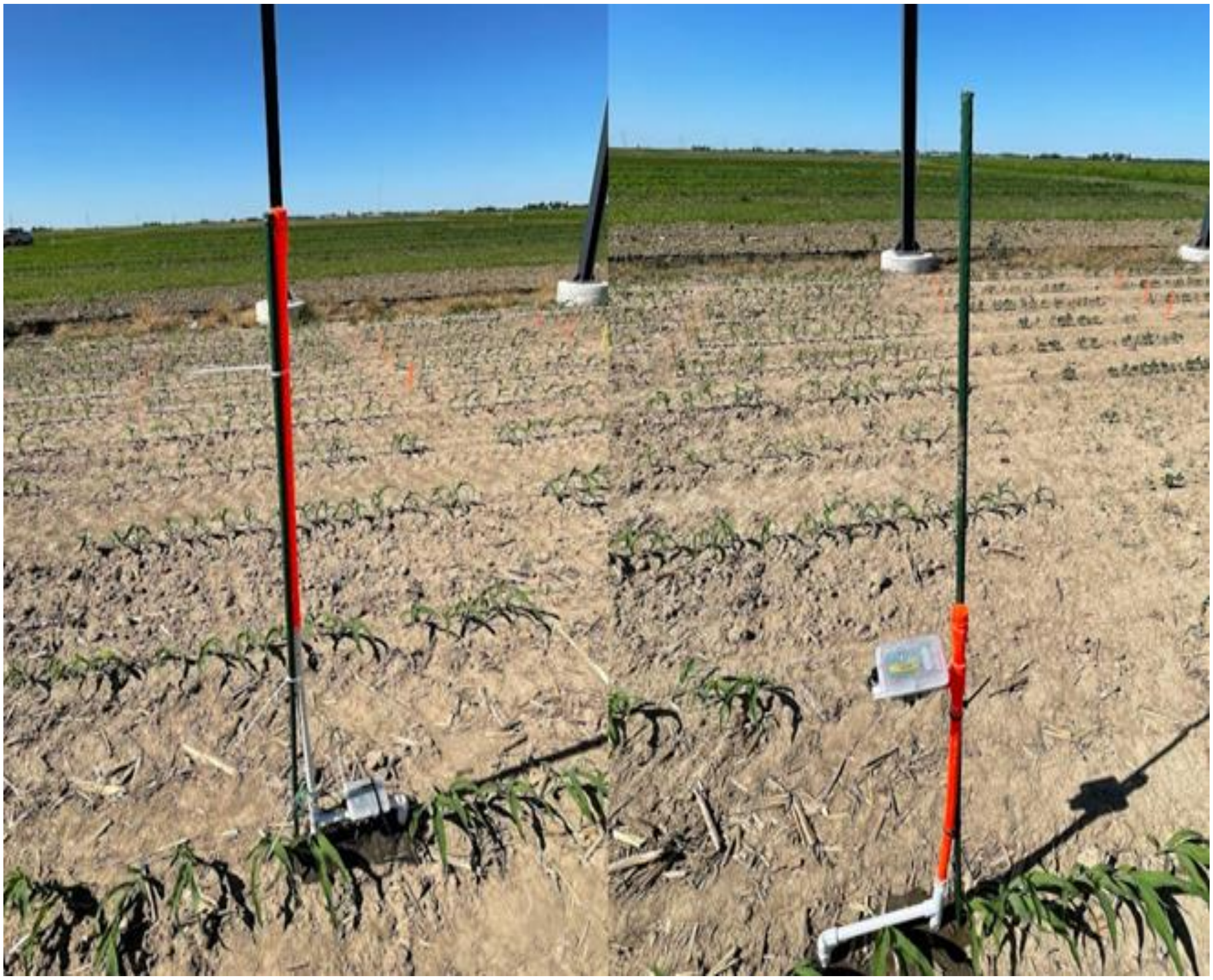
4.5.1 ACRE redeployment description (Corn)

The ACRE redeployments are labeled Ag sensor 3 (0.5' ft) and Ag Sensor 5 (1.5' ft) on the map below, shown with communication distance from the LoRAWAN gateway network. The Ag sensor 3 and Ag sensor 5 redeployed consist of the same type of sensors (4 external (2-Temperature- thermocouples+2- Soil moisture-resistive) + 1 inbuilt light sensor). The distance of the sensor nodes Ag Sensor 3 and Ag sensor 5 are 500.88 m, 500.27 m apart from the LoRAWAN gateway network. Communication range and orientation height of redeployed sensors were purposefully changed by the researcher to understand the impact on battery power consumption and received signal strength. Communication range and orientation height are the factors which might be related to battery power consumption of redeployed sensors as informed by ISM model and content analysis of interview data. These factors are considered for statistical analysis to understand the variation in sensor node battery power consumption and received signal strength index which might be critical for cost-effective maintenance decisions.



Picture 4.2: Ag Sensor 3 (500.88 m) & Ag Sensor 5 (500.27 m) location of redeployments

The picture above shows the location of redeployments at the Agronomy Center for Research and Education. The Low power Wide Area Network (LoRAWAN) gateway tower location is marked mentioning distance from the Ag Sensor 3 and 5. Communication range distance of redeployed sensor nodes is a decision variable which might be related to battery power consumption, data transfer rate and received signal strength index.



Picture 4.3: Ag Sensor 3 (0.5’ ft) & Ag Sensor 5 (1.5’ ft) orientation of redeployments

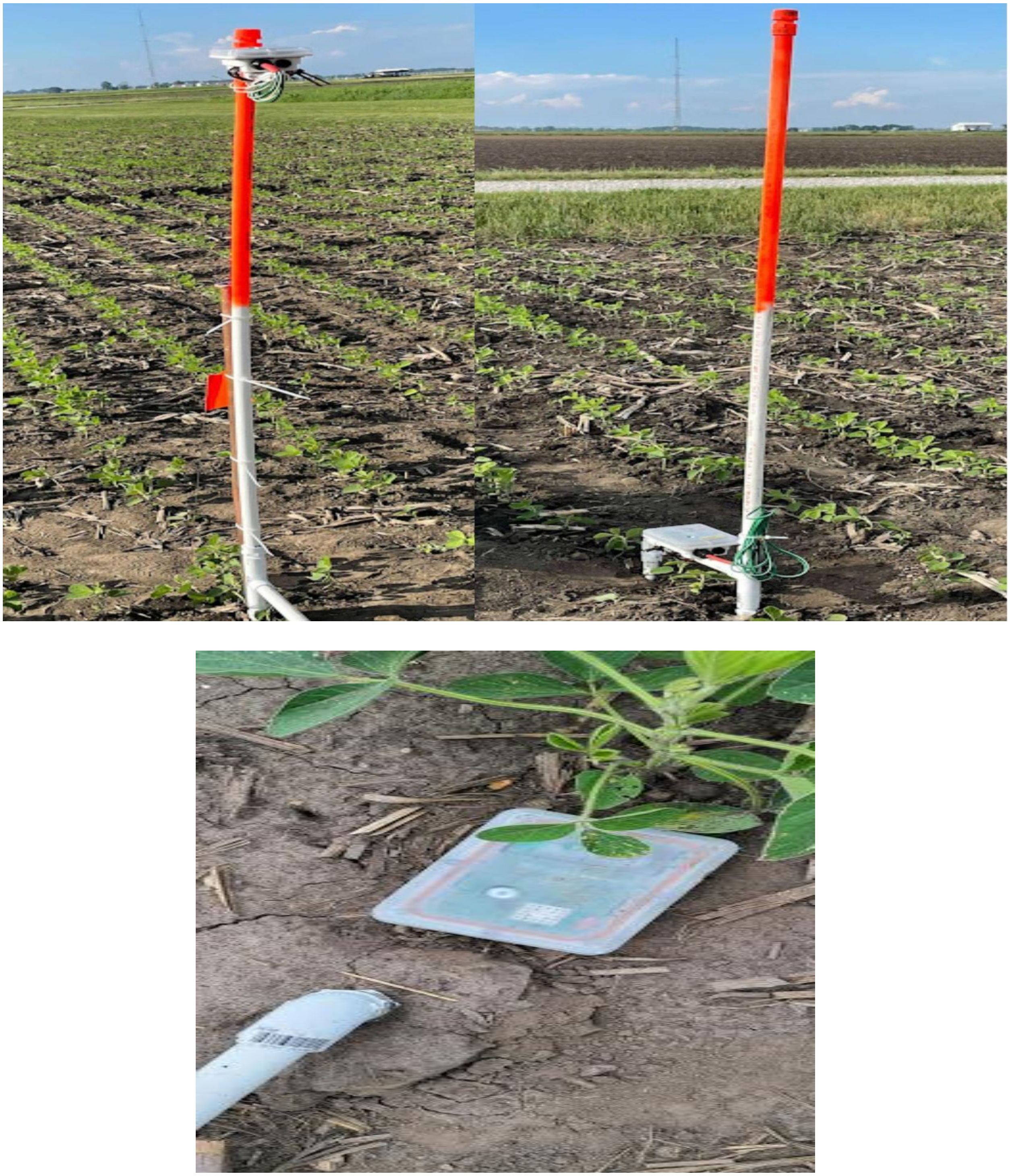
The pictures above show the redeployments orientation height of Ag sensor 3 (0.5’ ft) left and Ag sensor 5 (1.5’ ft) in the corn plot near the gantry at ACRE. The Ag Sensors 3 & Ag sensors 5 were integrated with Things board cloud as described in the section 4.4.2. (see Figure 4.9). The real time performance data for the variables (Received Signal Strength Index (RSSI), Signal to Noise Ratio (SNR), Battery Voltage (BV), Data Rate (DR)) are shown in the following section with the statistically correlation analysis for empirical validation of the ISM model. The analysis of variance (ANOVA) conducted for Battery Voltage (BV), Data Rate (DR), Communication Range (CR), Received Signal Strength Index (RSSI) and Signal to Noise Ratio (SNR) described in the following sections might be critical to understand the significant factors for variation in battery power consumption of sensor nodes.

4.5.2 ACRE redeployment description (Soybean)

The location of Ag Sensors 4 (450.32 m) and 2 (420.50 m) are marked on the maps shown below at the Soybean plot.

Picture 4.4: Ag Sensor 4 (450.32 m) & Ag Sensor 2 (420.50 m) location of redeployments

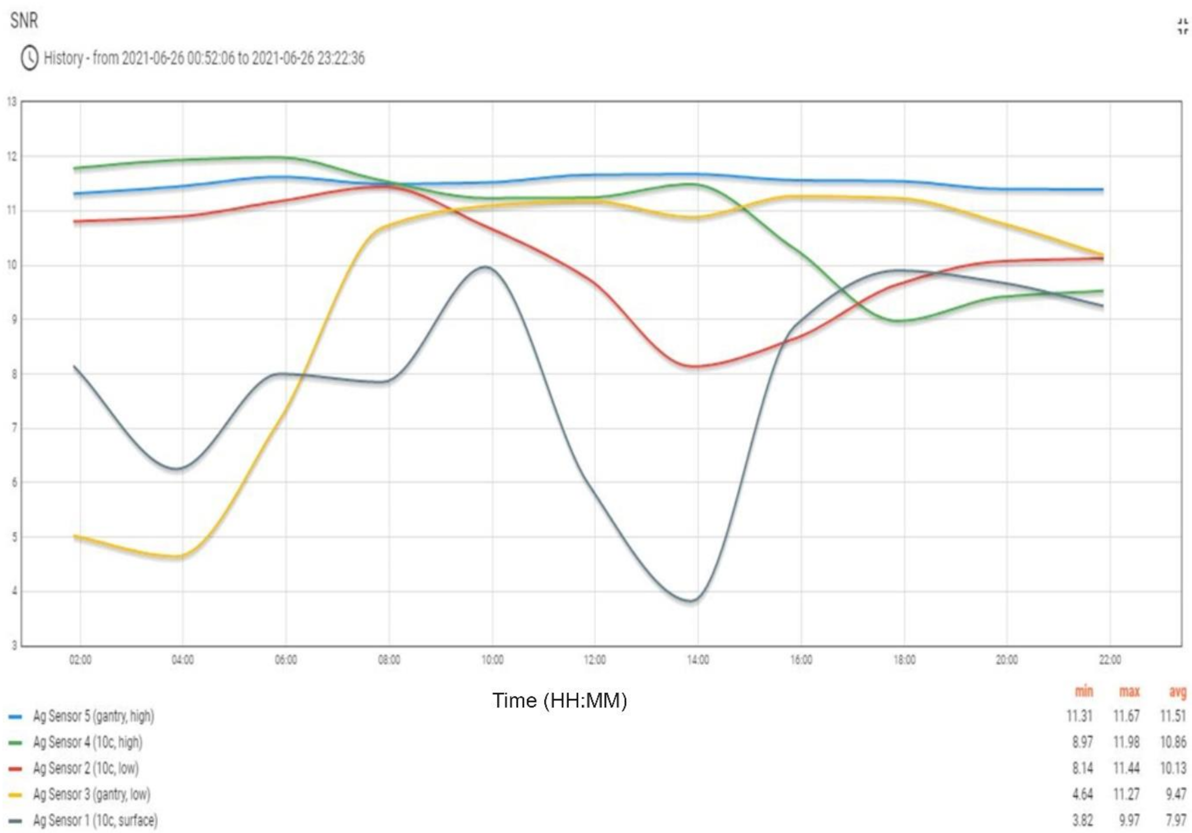
The Ag sensors 2 & 4 were deployed in the Soybean field plot as shown in the pictures (see Picture 4.4) with the distance marked from the LoRAWAN gateway tower. The Ag sensor 1 is a surface type sensor that consists of inbuilt (Temperature, Soil moisture & Light) sensors. The orientation height of sensors deployed is shown in the following picture.



Picture 4.5: Ag Sensor 4 (6’ ft), Ag Sensor 2 (0.5’ ft), Ag Sensor 1 (surface) orientation of redeployments

4.5.3 Real time data (SNR, RSSI, BV, DR) dashboard- Ag Sensors (1-5)

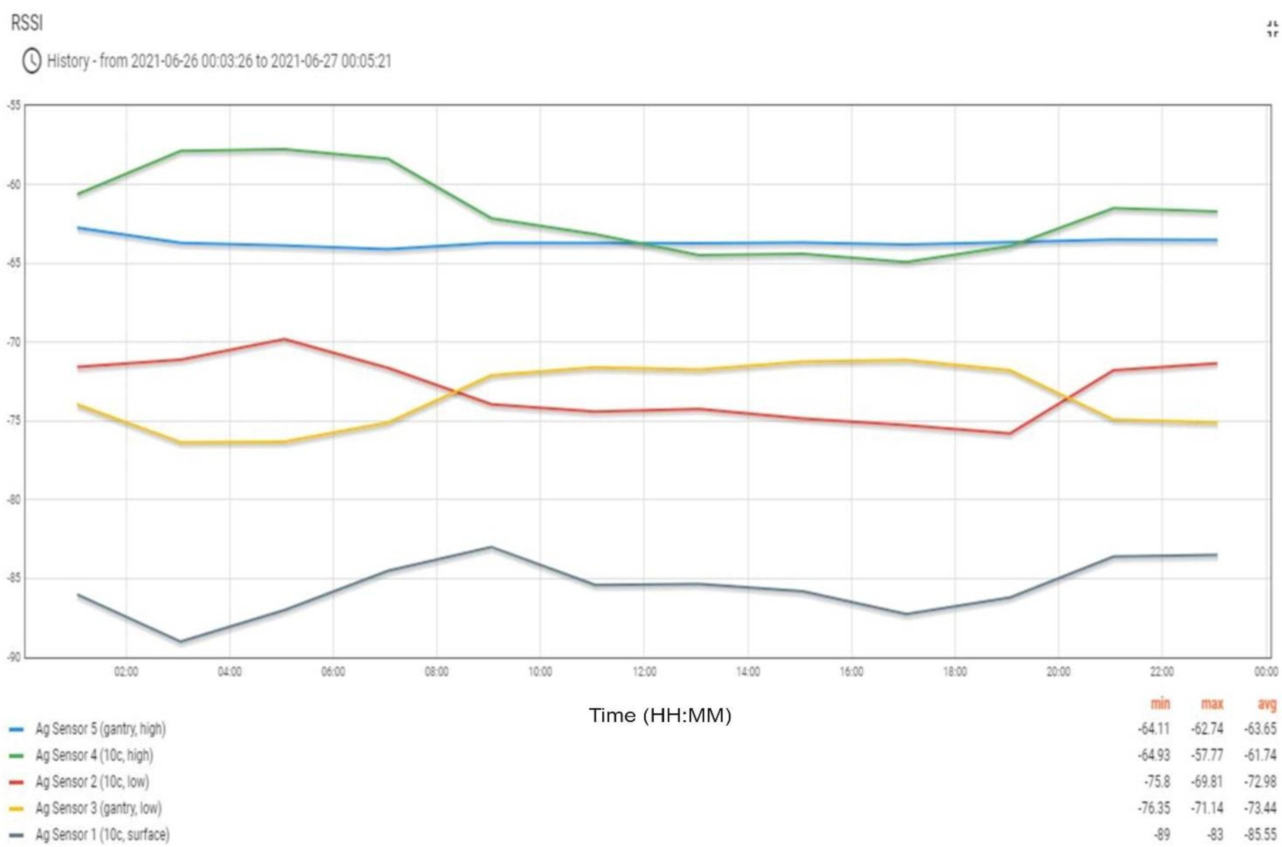
The Signal to noise ratio (SNR) real time data highlighted in Picture 4.6. is for a day (12.00 am to 12.00 pm) after sensors were deployed and 1st day of growing season with almost no-canopy (see Picture 4.6) in the field. Signal-to-Noise Ratio (SNR) is the ratio (difference) between the received signal power and the noise floor power level. Typical LoRa SNR values are between -20 dB and +10 dB (Gitijah, 2019). A value closer to +10 dB means that the received signal is less corrupted (Dolha, Negirla, Alexa & Silea, 2019).



Picture 4.6: Real time series data dashboard for Signal to noise ratio (SNR)

The variation between the SNR values for Ag Sensors (1-5) might be due to Communication Range (CR) distance, Received Signal Strength Index (RSSI), orientation height of sensor deployment and canopy growth as highlighted in the literature (Xu et al., 2011). The correlation analysis highlighted in Figure 4.12 explains the correlation of SNR with Communication Range distance and Received Signal Strength Index.

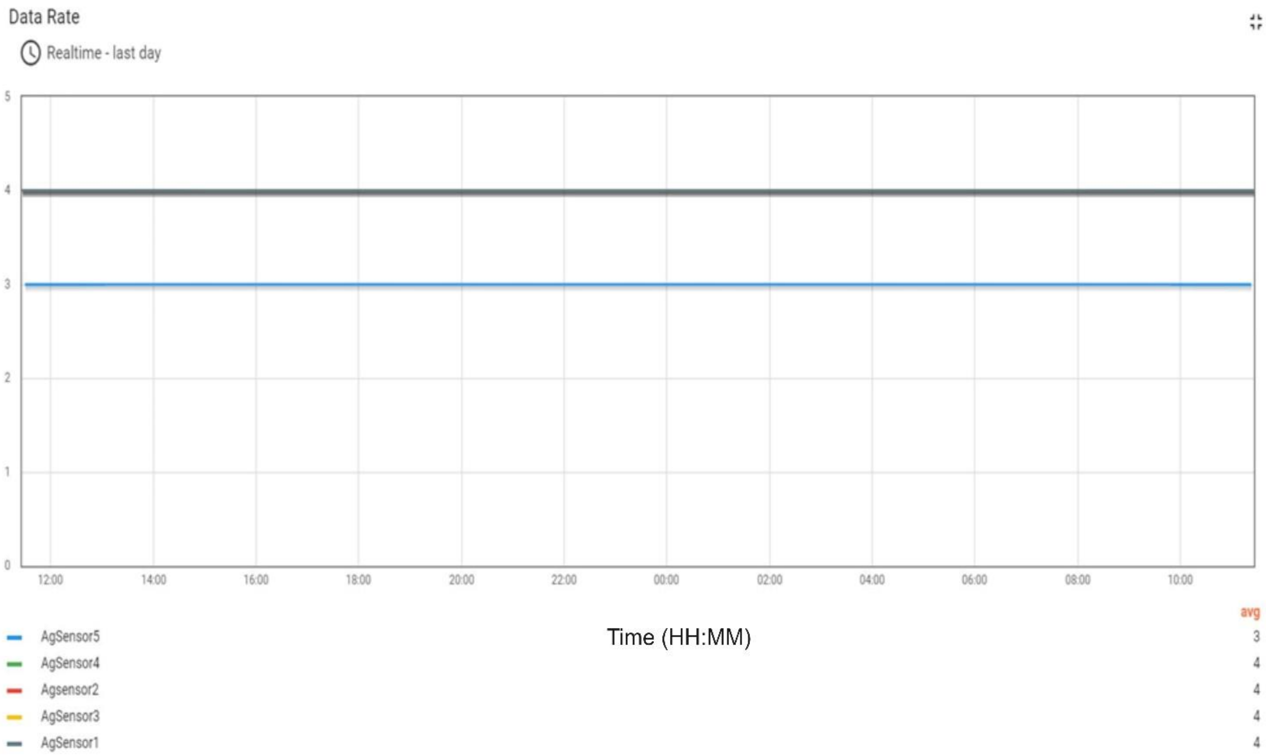
The researchers worked to empirically explore the variation in Received Signal Strength Index after considerable amount of canopy growth and orientation of deployment as box plots discussed in section 4.6.2. The Received Signal Strength Indication (RSSI) is the received signal power in milliwatts and is measured in dBm. LoRa typically operates with RSSI values between -30 dBm and -120 dBm. RSSI = -30 dBm is a very strong signal and -120 dBm is a very weak signal (Gitijah, 2019; Dolha, S. et al., 2019; Chaudhari & Borkar, 2020). The variation in the RSSI value for the Ag Sensors 1-5 might be explained by the variable factors (Communication Range (CR), Signal to Noise Ratio (SNR), Data Rate (DR)) due to canopy coverage or orientation height of deployment (Xu et al., 2011). The following sections explore the correlations amongst the variables measured (RSSI, SNR, CR, BV) using real-time data from the sensors.



Picture 4.7: Real time series data dashboard for RSSI.

The RSSI real time data dashboard shown above in picture 4.7 is for a day (12.00 am to 12.00 pm) after sensors are deployed and the 1st day of growing season.

The real time dashboard for Data Rate (DR) is highlighted in Picture 4.8. The Data Rate (DR) depicted in the real-time data dashboard is the Adaptive Data Rate (ADR). The Adaptive Data Rate (ADR) is a mechanism for optimizing data rates, airtime, and energy consumption in the network.

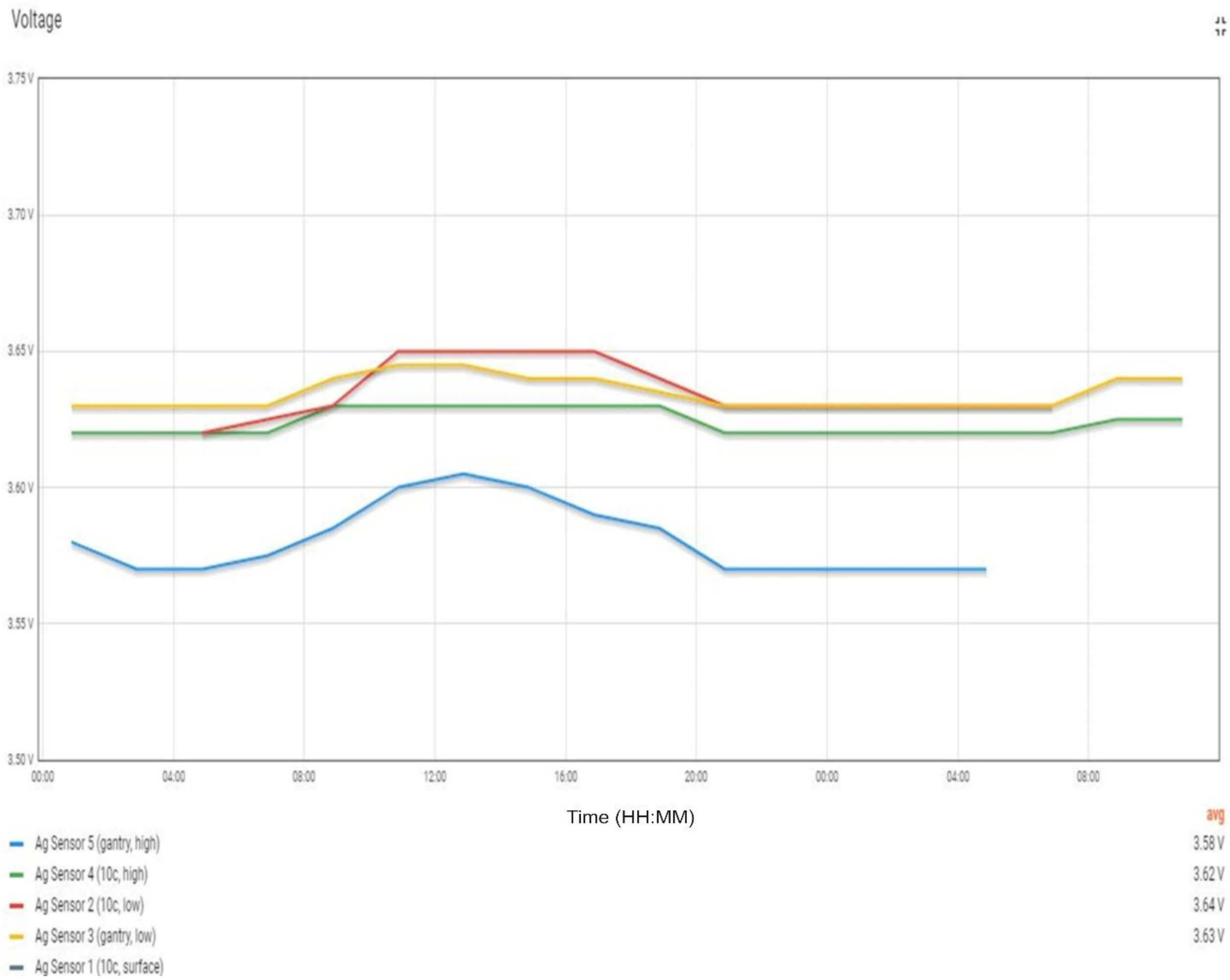


Picture 4.8: Real time series data dashboard for Data Rate.

Adaptive Data Rate can optimize device power consumption while ensuring that messages are still received at gateways. When the ADR is in use, as in the case of Ag Sensors 1-5 deployed, the network server will indicate to the end device that it should reduce transmission power or increase data rate. End devices which are close to gateways should use a lower spreading factor and higher data rate, while devices further away should use a high spreading factor with low Data Rate (DR) as it optimizes power consumption and increases network capacity (Kufakunesu, Hancke & Abu-Mahfouz, 2020)

The real time data dashboard for the operational Battery Voltage (BV) of Ag Sensors 1-5 is shown in picture 4.9. The variation in the operational battery voltages for the Ag Sensors 1-5 might be due to variation in Received Signal Strength Index (RSSI), Signal to Noise Ratio (SNR), Data Rate (DR), and Communication Range (CR) as highlighted in the literature (Pukrongta &

Kumkhet. 2019 October; Davcev et al., 2018). The researchers explain the variation in Battery Voltage (BV) using ANOVA on 2500 data points from the real time data obtained for a day after sensors were deployed and on the 1st day of growing season with almost no-canopy (see pictures 4.3, 4.5).



Picture 4.9: Real time series data dashboard for Battery Voltage.

The variation in the operating Battery Voltage (BV) for Ag Sensors 1-5 might impact the Battery life as power consumption increases for Lithium-Ion batteries per the operating voltage and Battery life curve highlighted in Figure 4.11. The variation might be due to factors Communication Range (CR), Data Rate (DR), Received Signal Strength Index (RSSI) and Signal to Noise ratio (SNR) as empirically analyzed in section 4.6.

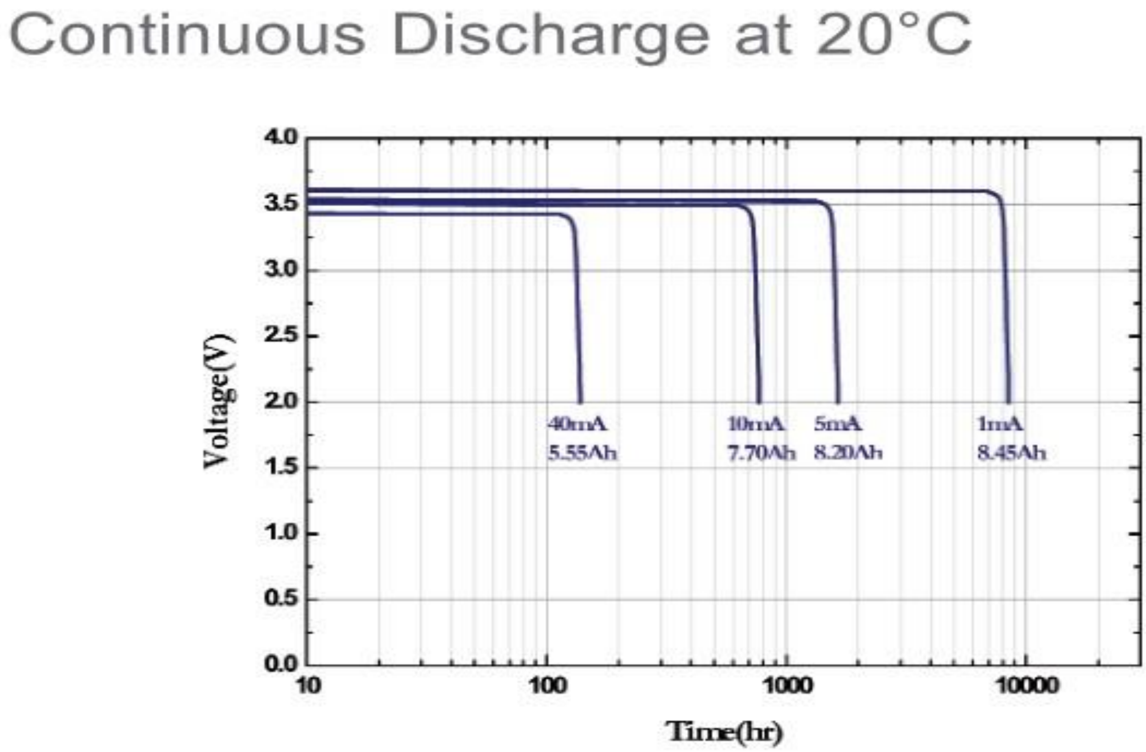


Fig. 4.11: Operating Battery Voltage vs Battery life for Lithium-Ion batteries
(Yu, Q. Q., Xiong, R., Wang, L. Y., & Lin, C. 2018)

This potentially means that for the Ag Sensor 5 operating at less average battery voltage 3.58 volts might draw more current for the same amount of power transmission signal, resulting in more discharge of battery reducing the battery life highlighted in the literature (Raj & Steingart, 2018; Knight, Davidson & Behrens, 2008). The researchers in this study empirically explore the BV variation using ANOVA considering the potential variables (Communication Range (CR), Received Signal Strength Index (RSSI), Signal to Noise Ratio (SNR) & Data Rate (DR)) identified in the literature and findings of Focused group interviews to explain the variation in the Battery Voltage (BV) for the deployed IoT sensors.

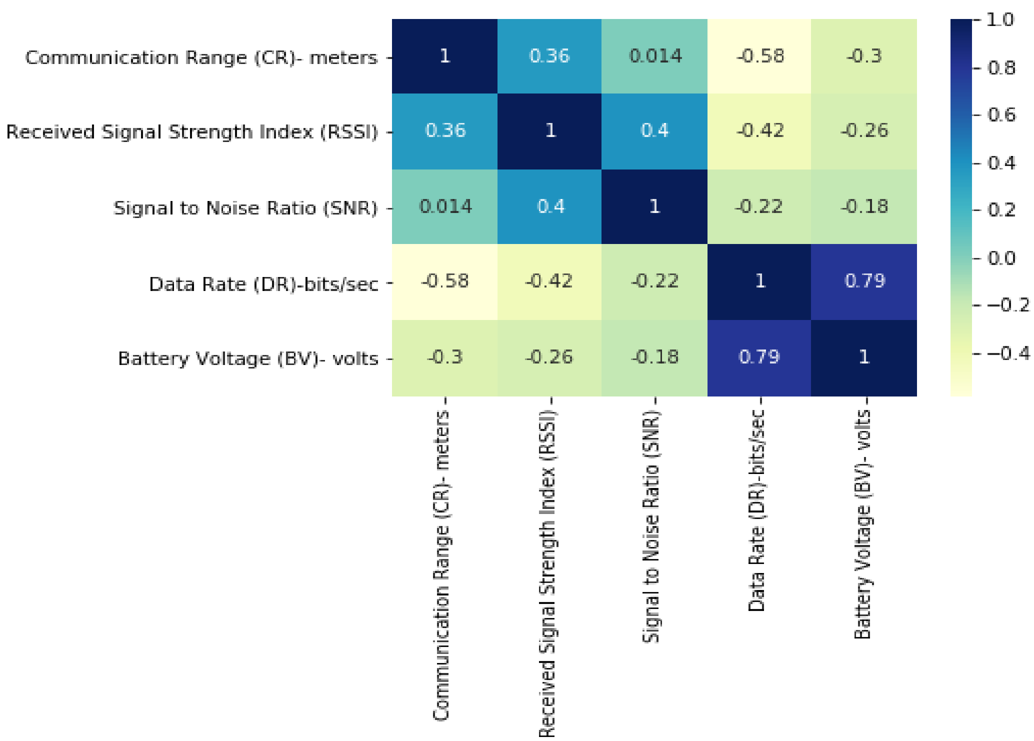
4.6 Empirical Validation of Interpretive Structure Model (ISM)- Correlation Analysis

The real time data from the Ag sensors 1-5 was analyzed for the variables (Communication Range (CR), Data Rate (DR), Battery Voltage (BV), Signal to Noise Ratio (SNR) & Received Signal Strength Index (RSSI)). The data set consists of 2505 data points, 501 from each of the 5 sensors deployed (Ag Sensors 1-5) during the same period i.e., after sensors are deployed and 1st day of growing season with almost no-canopy (see Picture 4.3,4.5) in the field. The data is analyzed for correlation heat map in Python Jupyter notebook, highlighting the Pearson correlation coefficients. The following code was entered to read and generate the correlation map in Python Jupyter notebook.

```
import pandas as pd
df=pd.read_excel("C:\\Users\\User\\Desktop\Ag Sensors 1-5 no canopy.xlsx")
sns.heatmap(df.corr(), cmap="YlGnBu", annot = True)
plt.show()
```

Picture 4.10: Python code used for plotting correlation matrix heat map.

The Pearson correlation coefficient matrix heat map shown in the Picture 4.11, highlights the measure of linear relationship between two variables. The value varies between -1 to +1 and highlights the relationship strength in terms of association and should not be interpreted as cause and effect as mentioned in the literature (Taylor, 1990). The values ≤ 0.35 are generally considered to represent weak correlations, 0.36 to 0.67 moderate correlations and 0.68 to 1.0 high correlations according to the literature (Taylor, 1990 & Khamis, 1989).



Picture 4.11: Correlation matrix heat map

There is weak positive correlation (0.014) between Signal to Noise Ratio (SNR) and Communication Range (CR) distance this might be due to no-canopy in the plain field as there was not much signal loss of transmission due to noise and interference, thereby validating the literature for static agriculture IoT sensors application (Xu et al. 2011; Pukrongta & Kumkhet, 2019 October; Navarro, Costa & Pereira, 2020). The relationship between Received Signal Strength Index (RSSI) and Communication Range (CR) is moderately positive (0.36) in the absolute values of RSSI which means with the increase in communication distance more power transmission should be there to receive the signal due to increased distance between sensor node and gateway and mentioned in the literature (Xu et al. 2011; Dolha et al. 2019). The relationship between Signal to Noise ratio (SNR) and Received Signal Strength Index (RSSI) is moderately positive (0.40), highlighting the increase in signal to noise ratio, leads to a moderate increase in received signal strength index that might also vary with communication range distance.

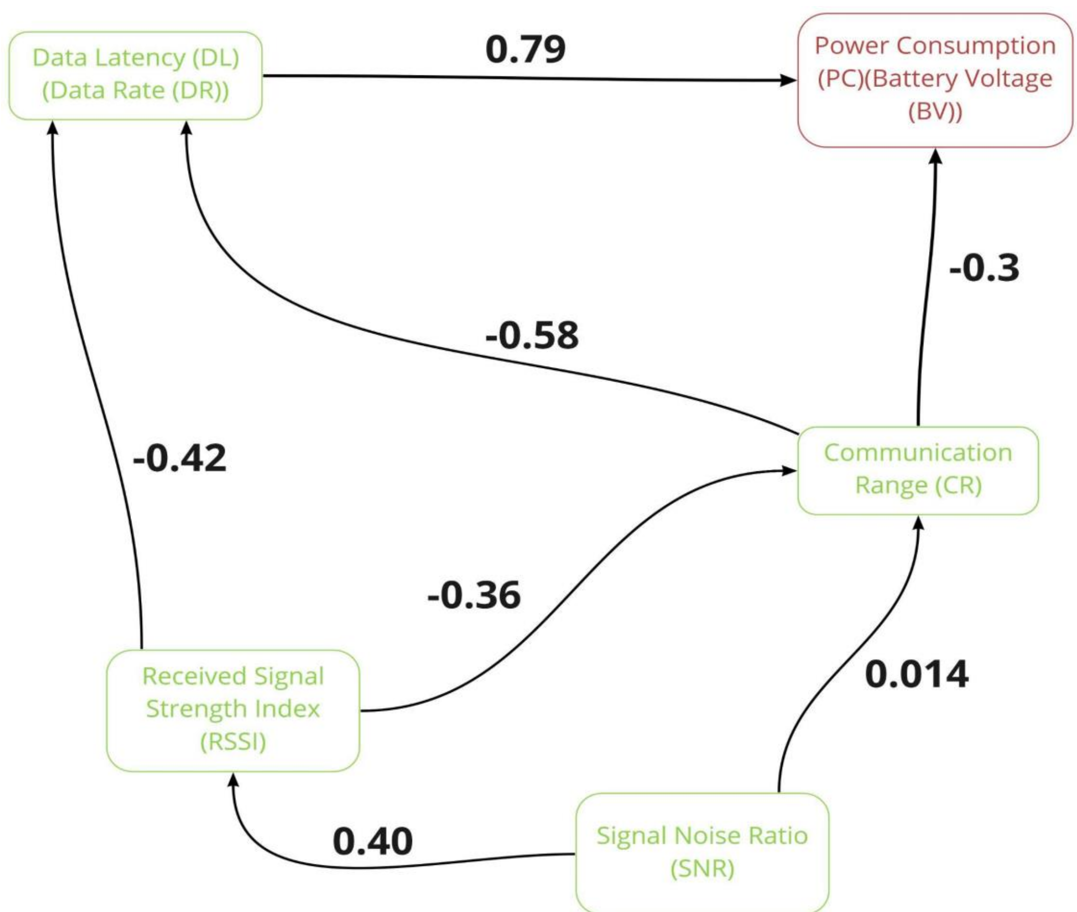


Fig. 4.12: Empirical validation of ISM model with correlation analysis

The Data Rate (DR) has strong positive correlation (0.79) with Battery Voltage (BV), which means increase in Data Rate (DR) increases operating Battery Voltage (BV) of the sensor, node, decreasing the discharge current and increasing the battery life of the sensor node. Communication Range (CR) and Data Rate (DR) have moderately negative (-0.58) coefficients where Communication Range (CR) distance increase leads to decrease in Data Rate (DR), which is there for Adaptive Data Rate in static IoT sensors highlighted in the literature (Kufakunesu, Hancke & Abu-Mahfouz, 2020). The following section assesses the significance of variables (CR, DR, SNR, RSSI) using multivariate ANOVA analysis to explain the variation in Battery Voltage (BV) used as a Power Consumption (PC) metric in this study for Lithium-Ion batteries.

4.6.1 Analysis of Variance for Battery Voltage (BV) before canopy growth

The variation in the Battery Voltage (BV) is critical to analyze from a variable cost and battery life context. This section explains the variance in operating Battery Voltage using real time data (n=2505) from the deployed Ag Sensors (1,2,3,4,5) reported for a 1st day of growing season with almost no-canopy (see Pictures 4.3,4.5) in the field. The findings highlighted (see Table 4.6) for the Analysis of Variance (ANOVA) with Battery Voltage (BV) as dependent variable and independent variables (Communication Range (CR), Received Signal Strength Index (RSSI), Signal to Noise Ratio (SNR) and Data Rate (DR)). The results of the analysis (see Table 4.6) highlight a R^2 value 0.665, which signifies the percentage of variation i.e., 66.5 % in the dependent variable (BV) is explained by the independent variables (CR, DR, RSSI, SNR) or predictors. The equation below highlights the predictor and correlations coefficients for the ANOVA output shown in (Appendix C).

$$BV = 3.34 + .000153 \cdot CR + .000157 \cdot RSSI + .0000503 \cdot SNR + .0559 \cdot DR$$

Table 4.6: Multiple Linear Regression analysis for variance

Y= BV, X= CR, RSSI, DR, SNR

Regression Statistics	
Multiple R	0.82
R Square	0.665
Adjusted R Square	0.665
Standard Error	0.014
Observations	2504

Communication Range (CR), Received Signal Strength Index (RSSI) and Data Rate (DR) resulted to significant variables, have p values $\leq$ 0.05 (assuming $\propto$= 0.05). The significance of the variables (CR, RSSI & DR) in explaining variation in dependent variable (BV) is substantiated by the findings of the previous section where moderate to strong correlations were exhibited between dependent variable and independent variables (see Figure 4.12). Signal to Noise ratio is not a significant factor with a p value=0.65 $\geq \propto$=0.5. This might be explained by the reason that there was no canopy in the field for the real time data analyzed and therefore there is not much signal losses due to open fields with no building or canopy growth. The researchers explored the variance in the Battery Voltage (BV) from the real time data reported from the deployed Ag Sensors 1-5 for a day (30th day of the growing season) after the considerable canopy growth for checking the impact of canopy biomass on BV (see Picture 4.12). The analysis was conducted to explore the variation using (BV) as a dependent variable and (CR, DR, RSSI & SNR) as independent variables. The residual value 2499 in the Table 4.6 highlights that lot of degrees of freedom values might be left over.

4.6.2 Analysis of Variance for Battery Voltage (BV) after canopy growth

The considerable canopy growth (see Picture 4.12) might interfere with the received signals due to the canopy biomass above the sensor nodes, highlighted in previous studies (Xu et al. 2011; Raj & Steingart, 2018). Therefore, the researchers tried to further explore the variation explained with Battery Voltage (BV) as dependent variable and Communication Range (CR), Received

Signal Strength Index (RSSI), Data Rate (DR), Signal to Noise Ratio (SNR) as independent variables. The analysis might be used for future research to explore the impact of canopy growth on battery power consumption of sensor nodes.

Picture 4.12: Ag Sensor 5 (left- corn plot) & Ag Sensor 3 (right- soybean plot) with considerable growth of canopy (30th day of the growing season)

The variance in the Battery Voltage (BV) after considerable growth of canopy was just 6.5 % ($R^2 = 0.064$) explained by the independent variables (CR, SNR, RSSI & DR). The Analysis of Variance (ANOVA) applied using real time data (n=2505) points from the Ag Sensors 1-5 on the 30th day of growing season where the corn plant can grow approximately 4 feet tall and soybean plant 1 feet tall (Tucker, Elgin, McMurtrey, & Fan, 1979). The change in the variation from 66.5% to 6.5% explained by the independent variables (CR, SNR, RSSI & DR) may be due to the considerable amount of canopy growth as highlighted in the study (Xu et al., 2011). The equation below highlights the predictor and correlations coefficients for the ANOVA output shown in (Appendix C).

$$BV = 3.64 - 0.000008 \cdot CR - 0 \cdot 0005758 \cdot RSSI - 0.0001175 \cdot SNR - 0.0099 \cdot DR$$

Table 4.7: Multiple Regression Analysis for analysis of variance

Y= BV, X= CR, RSSI, DR, SNR

Regression Statistics	
Multiple R	0.26
R Square	0.065
Adjusted R Square	0.064
Standard Error	0.020
Observations	2504

Received Signal Strength Index (RSSI) and Data Rate (DR) are still significant factors explaining almost 6.5 % variation in the Battery Voltage (BV). This variation might be explained by considerable growth in canopy after a month of seeding. The variation in the Received Signal Strength Index (RSSI) by sensor nodes due to canopy biomass around them might interfere with the signal as highlighted in the studies (Xu et al. 2011; Dolha et al. 2019). Therefore, researchers explain the variation in Received Signal Strength Index (RSSI) comparing the RSSI values for the data sets (see Appendix B) before (no-canopy) and after (30^{th} day of growing season) where considerable canopy growth resulted in the comparison, shown by boxplots in the following section for the data sets of Ag Sensors 1-5.

4.6.3 Received Signal Strength Index (RSSI) analysis before and after canopy growth

The Received Signal Strength Index (RSSI) for the real time data was analyzed (n= 2505, Ag Sensors 1-5) during the 1st day of the growing season. The LoRaWAN typically operates with

RSSI values between -30 dBm and -120 dBm. RSSI = -30 dBm is a very strong signal and -120 dBm is a very weak signal (Gitijah, 2019, Dolha, S. et al., 2019, Chaudhari & Borkar, 2020).

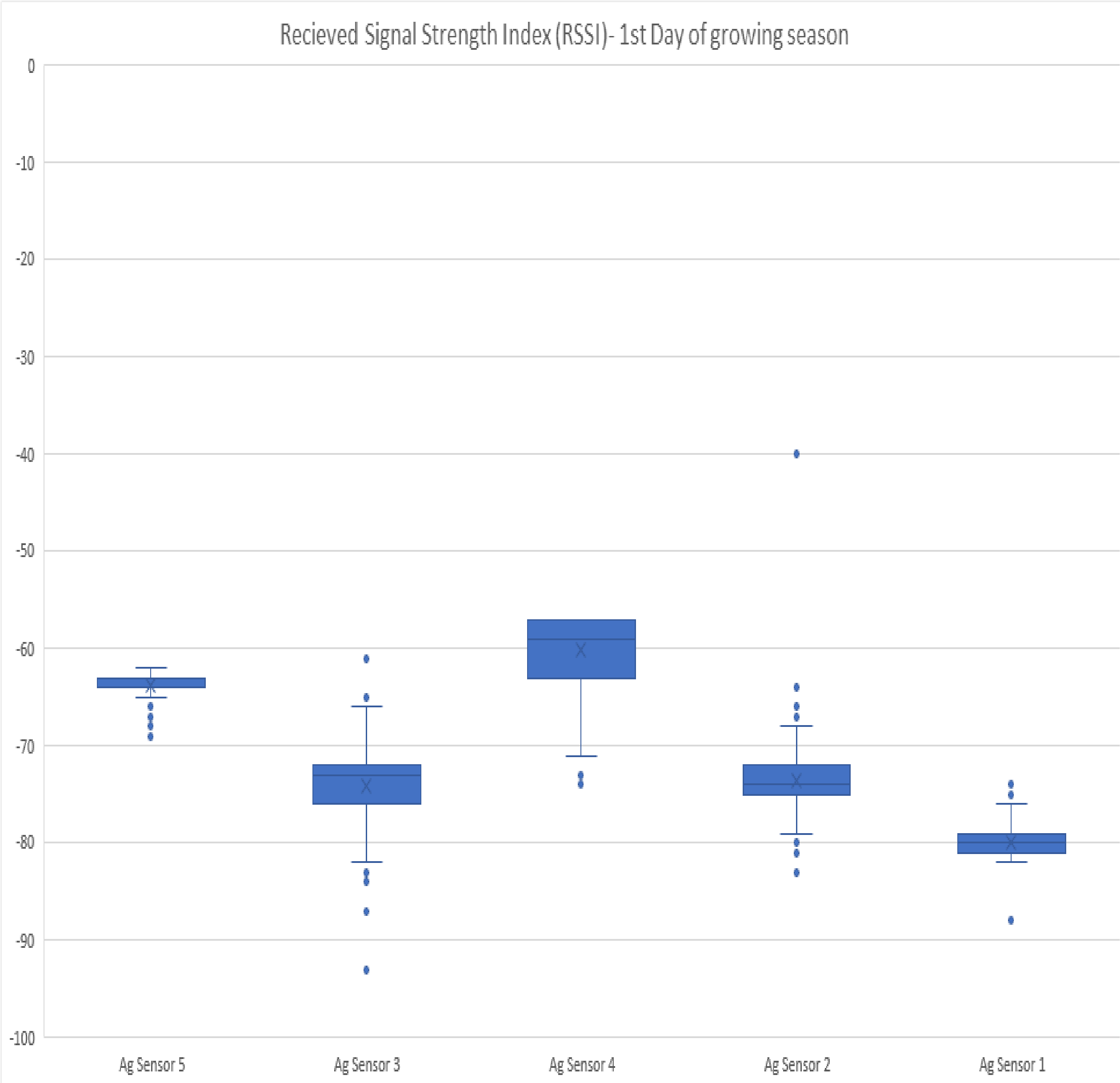


Fig. 4.13: Box plots for Ag Sensors Soybean plot- 1 (Surface), 2(0.5'ft), 4(6' ft)
Ag Sensors Corn plot- 3 (0.5'ft), 5(6' ft)

The box plot in Figure 4.13 highlights the variation between and within the RSSI values for the Ag Sensors 1-5. The Ag Sensors (1,2,4) are deployed in the soybean plot (see Picture 4.5) with different orientations i.e., Ag sensor 1- surface (buried in ground), Ag sensor 2 (0.5'ft from ground), Ag sensor 4 (6'ft from ground). The Ag Sensors (3,5) are deployed in the corn plot (see picture 4.3) with different orientations i.e., Ag sensor 3 (0.5'ft from ground) and Ag sensor 5 (6'ft from ground). The significance of developing boxplots is to propose a future research prospect based on understanding variation of RSSI with orientation and canopy growth. The variation in the RSSI values between the Ag Sensors 1-5 might be due to orientations as we can clearly see in the box plot that Ag Sensor 5 & Ag Sensor 4 are deployed 6' ft from the ground having better signals average RSSI values (-64, -57) as compared to Ag Sensors 3,2,1 having weak average RSSI values (-74, -76, -80). This might be critical for deploying sensors and receiving appropriate communication signals. The Received Signal Strength Index of the deployed sensors might become weaker with the canopy growing season, as implied by the research findings. Potential future research questions might explore the impact on operating Battery Voltage (battery power consumption) of sensor nodes with weak signal received as canopy grows beyond 1 month. These findings might be critical to implement a lean-green decision making for deploying sensors saving on costs associated with battery power consumption. The other interesting potential future research might explore and test the findings of this research in other Autonomous precision agriculture applications.

CHAPTER 5. CONCLUSIONS, FUTURE WORK & RECOMMENDATIONS

This chapter describes the conclusion summary of the research findings describing the potential implications, future research work and recommendations for developing lean-green Internet of Things (IoT) wireless sensors data pipeline.

5.1 Research Questions

Based upon the findings of the thesis, this section summarizes the results for research questions, methodology followed and potential implications for stakeholders (Row crop producers, Precision Agriculture practioners and Digital agriculture technology consultants).

RQ1: What are Lean and Green practices in the context of Indiana row crop production?

The findings of the structured literature review highlights Lean and Green practices in context of Indiana row crop production. Precision Agriculture practices are adopted by producers through Lean-Green drivers namely Delivery performance, Profitability, Operational Cost, Overall productivity, Hazardous Waste Reduction, Information Sharing and User-end experience (user satisfaction). Lean-Green drivers identified might help producers to benchmark agricultural operations for optimized usage of farm inputs (Fertilizers, Water resources, Labor productivity & Farm Machinery).

Another finding highlights Precision Agriculture practices such as variable rate fertilizer (39 %), variable rate pesticide (8%), variable rate irrigation (4 %), cloud-based data analytics (21 %) and telematics (10 %) are the Internet of Things (IoT) Precision Agriculture technologies having low adoption rates among Indiana row crop producers. The finding suggests that there is a gap in the literature for understanding the barriers leading to low adoption of IoT based Precision Agriculture technologies. There is a need to fill this gap for creating body knowledge leading to improved adoption of Precision Agriculture practices among Indiana row crop producers.

RQ2: What are barriers to adoption of Precision Agriculture technologies among Indiana row crop producers?

Structured Literature Review followed by content analysis identifies the barriers to adoption of IoT based Precision Agriculture technologies among Indiana row crop producers. The findings highlight barriers based on Cost (Return on Investment), Power consumption, sensor nodes integration, Communication range limitations, Data latency (Data Transfer) requirements, Data interoperability, Data scalability, Data storage, Data processing & User-Interface of cloud storage. The subsequent finding suggest barriers are classified into three layers of IoT wireless sensors framework for Precision Agriculture technologies i.e., Perception layer (Type of Sensors, Sensor node integration, Power consumption of sensor node), Communication Layer (Communication range limitations, Costs, Data latency, Data scalability, Power consumption) and Data Processing & Application layer (Data scalability, Data storage, Data processing, Data interoperability & User-Interface).

The findings fill the knowledge gap and might inform producers about barriers to adoption of IoT based Precision Agriculture technologies. The barriers identified were used to develop semi-structured focused groups interview questions for further understanding and establishing relationships developing theoretical framework for Lean and Green adoption.

RQ3: How might a Lean and Green Internet of things (IoT) wireless sensors framework be developed for the improved adoption of Precision Agriculture technologies among Indiana row crop producers?

The semi-structured focused group interviews were conducted with subject matter expertise (SME's), (N=18) in IoT based Precision Agriculture practices to understand and define decision variables related to barriers following content analysis approach. Interpretive Structural Modeling (ISM) approach was used to develop a model describing relationships among decision variables (Cost, Power Consumption, Communication Range, Data Latency, Data Scalability, Data Storage, Data Processing, Data Interoperability, Type of Sensors, Type of Wireless Communication, Type of Precision Application). The ISM model highlighting relationships between variables Cost, Power Consumption, Data Scalability, Data Storage and Type of Wireless Communication was validated and informed design improvements in redeployment (sensor node B). The findings based on comparison of action research deployments reported design improvements in redeployment from initial deployment based on finding Data Interoperable open-source (see Appendix B) Things board network cloud storage reducing variable costs by $204. Battery power consumption cost decreased by 60 % with decrease in Data scalability from 8 sensors (initial deployment) to 4 sensors (redeployment). Low Power Wider Area Network (LoRAWAN) wireless communication gateway integrated with Monitoring (Temperature, Humidity, Soil Moisture & Light) and Autonomous (GPS) sensors in redeployment is interoperable solution as compared to LoRA sub-edge radio which integrates with Monitoring sensors only. The implications of action research findings might inform producers, IoT Precision Agriculture practioners and researchers about cost effective, power efficient, data interoperable and open-source solution (see Appendix B) for IoT wireless sensors-based Precision Agriculture applications. The ISM model developed might help producers to understand the relationships between decision variables or barriers for Lean Green adoption.

A correlation model empirically validated the ISM model highlighting Battery Voltage (BV) (Power Consumption) for deployed sensors has strong positive correlation (0.79) with Data Rate (DR) and moderately negative correlations (-0.3, -0.26) with Communication Range (CR) and Received Signal Strength Index (RSSI). This finding implies that sensor nodes deployed at a longer distance from LoRAWAN communication gateway must run at lower Data Rate (DR) for low battery power consumption and is significant for cost effective maintenance decisions. The finding of boxplots highlighting variation in Received Signal Strength Index (RSSI) for sensors redeployed suggests orientation and canopy growth are the factors that might impact the signal strength which might be critical to explore for making maintenance decisions.

The findings of this thesis might inform row crop producers, Precision Agriculture practioners and technology consultants about cost and energy efficient design for Lean-green adoption of IoT based Precision Agriculture technologies. The ISM model developed might be used by different small-medium enterprises (SME's) to benchmark and establish key performance indicators for Lean-Green adoption of precision manufacturing IoT wireless sensor technologies.

5.2 Conclusions

Lean and Green operational barriers or variables identified for Internet of Things (IoT) based wireless sensors data pipeline framework through structured literature review are Cost (CT), Data Storage (DS), Data Scalability (DSC), Data Latency (Data Rate (DR)), Communication Range (CR), Data Processing (DP), Power Consumption (PC), Data Interoperability (DI), Type of Sensors (TS), Type of Wireless Communication technologies (TWC) & Type of Precision Agriculture application (TPA). The relationship between the variables developed through Interpretive Structural Model (ISM) is empirically validated (DSC, DS, DI, CT, TWC, CR, DR, PC) through comparison of action research deployments and statistical analysis.

Data Interoperable open-source cloud integration of Things network increased the data scalability in context of integrating different types of sensors i.e., Autonomous (GPS) & Monitoring (Temperature, Humidity, Soil Moisture & Light). Data scalability decreases with decrease in number of sensors integrated and so does the battery power consumption of the sensor node. Operating Battery Voltage (BV) of sensor nodes vary significantly with Data Rate (DR), Communication Range (CR) and Received Signal Strength Index (RSSI). Operating Battery Voltage (BV) of sensor nodes varies significantly with Communication Range (CR), Received Signal Strength Index (RSSI) and Data Rate (DR). Higher communication ranges and lower Data Rate (DR) decreases operating Battery Voltage (BV) of sensor nodes which might increase current withdrawals thereby increasing power consumption and decreasing battery life of sensor nodes. Growth in canopy and orientation of redeployed sensor nodes might impact the strength of received signals. Received Signal Strength Index (RSSI) is critical to evaluate for the redeployed sensors as it might decrease with canopy growth and orientation needed to be changed for the sensors deployed near the ground for stable working receiving appropriate signals.

5.3 Recommendations & Future Work

Power consumption of a sensor node increases with Data Scalability as highlighted by the findings of action research deployments. Therefore, it is relevant to identify the critical data or scale and type of sensors required based upon the type of precision agriculture application and type of wireless communication technology used for integration. Data interoperability depends upon Data storage and open-source cloud Things network is more interoperable in context of data storage and processing capabilities with integration of heterogeneous sensors (Monitoring & Autonomous) highlighted in the deployment of sensor node B. Open-source integration of sensor nodes with Things cloud network eliminated the substantial part of variable cost associated with subscription. Operating Battery Voltage of a sensor node varies with Communication Range distance from communication gateway network, Data Rate and Received Signal Strength Index. The sensor nodes deployed at wider distances might operate at lower Battery Voltage (BV) as compared to sensor nodes that are closer to the communication gateway network (LoRAWAN). Therefore, it is recommended through the findings of our research that as per low Data Rate requirements of Monitoring precision agriculture applications sensor nodes located at wider ranges from the communication gateway network should operate at lower Data Rate for same power consumption during signal transmission as also recommended and highlighted by recent study (Kufakunesu, Hancke, & Abu-Mahfouz, 2020). This recommendation is specifically for static sensor nodes deployed within 7 miles (maximum coverage range for LoRAWAN) with no considerable canopy growth on field. However, as the growing season proceeds Received Signal Strength Index (RSSI) decreases with canopy growth and sensors deployed below the canopy height might receive low signals as highlighted through research findings. Therefore, it is recommended changing the orientation of deployed sensors to keep them above the canopy biomass for receiving appropriate signals. The research questions that might be interesting to explore and complements the future research aspects are highlighted in Table 5.2. The variation of Received Signal Strength Index per day during the growing season of corn & soybean for LoRAWAN compatible sensors might be useful to explore through a broader impact study highlighting the loss of signal strength with canopy biomass. The other interesting research question that might be useful to explore is correlation between Received Signal Strength Index and battery Power Consumption in metric of sensor node battery life. The research findings highlight that there might be significant reduction in Received Signal Strength Index with canopy growth so it might be interesting to explore if there is any significant variation in power consumption by sensor node as well to predict battery life as it relates to significant variable cost. The research findings are limited to static sensor nodes for monitoring micro-climatic field conditions. Therefore, it might be potentially interesting to explore the battery life predictability for moving sensor nodes (GPS) and variation with Communication Range (CR) distance for

LoRAWAN compatible sensors. The table below highlights the potential future research questions and their potential implications.

Table 5.1: Future research questions and potential implications.

Future Research Questions	Potential Implications
How does the Received Signal Strength Index vary per day during the growing season of Corn & Soybean for LoRAWAN compatible agriculture sensors?	Predictability of maintenance decisions for sensor node orientation needed to be changed due to loss of signal strength with canopy growth.
How does battery life of a static sensor node vary per day during the growing season of Corn & Soybean for LoRAWAN compatible sensors?	Predictability of sensor node battery life for static monitoring applications with canopy growth per day.
How does battery life of a moving autonomous (GPS) sensor node vary with Communication Range distance for LoRAWAN compatible sensors?	Predictability of battery life for moving autonomous (GPS) sensor nodes and variation with Communication Range distance for LoRAWAN compatible sensors.
How Lean & Green IoT wireless sensors framework be developed for smart manufacturing applications?	Optimizing inputs, Logistics decision making, Benchmarking, and evaluating Lean-Green IoT systems for smart manufacturing.

Interpretive Structural Model developed through this research for Internet of Things (IoT) wireless sensors-based data pipeline might be used in logistics decision making, benchmarking technology adoption, and evaluating Lean and Green IoT systems for smart manufacturing. This might be a future research study exploring Lean and Green IoT wireless sensors framework for developing smart manufacturing applications. The potential implications by developing Lean and Green IoT framework for smart manufacturing systems might help to optimize inputs and resources through precision manufacturing. Lean and Green IoT wireless sensors framework might also inform precision technologists and practioners for cost and energy efficient adoption of IoT precision manufacturing applications.

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APPENDIX A. INTERVIEW SCRIPT

Hello, my name is ______________and I am a Purdue University graduate student conducting this focused group interview with (   ) on (date/time).

The purpose of this research study is to explore the lean (cost, power, data scalability, data processing and user-experience) and green (energy and hazardous waste reduction precision agriculture applications) Internet of things (IoT) wireless sensors framework for the adoption of precision agriculture applications (monitoring row crop diseases, smart irrigation, smart fertilizing, and farm-machinery efficient navigation) amongst row crop producers in Indiana region. A content analysis will be conducted through focused groups semi-structured interviews with subject matter experts in open-agriculture technological systems (OATS), Digital agriculture experts (Professors, Graduate Students & Purdue ACRE extension members). The findings of the content analysis from the focused group interviews will be used to inform the multiple Farm beats sensor boxes deployment at Purdue Agronomy Center for Research and Education (ACRE) farm facility following action research. The goals of this study are as follows:

1. Identify the different types of sensor combinations that can be used to gather the data for developing precision agriculture applications (monitoring row crop diseases, smart irrigation, smart fertilizing, and farm-machinery efficient navigation) for an average size row crop farm in the Indiana region.

2. Understand the efficient (cost, power, data scalability, data management) and effective (communication range, data latency, data interoperability, data processing) wireless communication technologies that can be integrated with sensors for developing precision agriculture applications (monitoring row crop diseases, smart irrigation, smart fertilizing, and farm-machinery efficient navigation) for an average size row crop farm in Indiana region.

3. Understand and identify the efficient (cost, power, data management) and effective (data latency, data interoperability and data management) data storage and processing application programming interfaces for developing precision agriculture applications (monitoring row crop diseases, smart irrigation, smart fertilizing and farm-machinery efficient navigation) for an average size row crop farm in Indiana region.

4. Understanding the dependencies of variables namely type of sensors, type of wireless communication technologies, no. of devices-data scalability, communication range, data latency, data interoperability of application programming interfaces with cost, power consumption and type of precision agriculture applications (monitoring & autonomous).

To participate in this research, we ask for approximately (1 hour) of your time through a guided semi-structured focused group interview. All research carries risks, but the risks associated with this study are minimal and no more than found day to day. The minimal foreseeable risks are that your identity might be accidentally repealed to parties other than the researchers, should there be a confidentiality breach. However, we are taking several measures to protect your identity. There are few direct benefits to you from participating in this research, but the research results will benefit: row crop farmers, digital agriculture practitioners and open agricultural technology researchers. This interview will be recorded for transcription as data collection for subsequent analysis. We do appreciate your time as your experience, background & expertise are critical to the success of this study.
Do you all consent to participating in this study? May we record our conversation?

Demographics

1. What is your educational background and current role in the organization you work?
2. What is your experience with digital agriculture?

Perception Layer (Types of sensors)

1. What are the different types of sensors that can be used to develop applications for monitoring row crop diseases on an average size farm in the Indiana region?
2. What are the different types of sensors that can be used to develop applications for smart irrigation applications on an average size row crop farm in the Indiana region?
3. What are the different types of sensors that can be used to develop applications for smart fertilizing on an average size row crop farm in the Indiana region?
4. What are the different types of sensors that can be mounted on farm- machinery for efficient navigation during planting and harvesting operations?

Communication Layer (Wireless communication technologies)

1. How can we efficiently (cost, power, scalability) and effectively (communication range, data latency, data storage and processing) integrate different types of sensors with wireless communication technologies for monitoring row crop diseases precision application on an average size farm in the Indiana region?

2. How can we efficiently (cost, power, scalability) and effectively (communication range, data latency, data storage and processing) integrate different types of sensors with wireless communication technologies for smart irrigation autonomous application on an average size row crop farm in the Indiana region?

3. How can we efficiently (cost, power, scalability) and effectively (communication range, data latency, data storage and processing) integrate different types of sensors with wireless

communication technologies for smart fertilizing autonomous application on an average size row crop farm in the Indiana region?

4. How can we efficiently (cost, power, scalability) and effectively (communication range, data latency, data storage and processing) integrate different types of sensors with wireless communication technologies for farm- machinery efficient navigation on an average size row crop farm in the Indiana region?

Data processing & application layer (Data storage, management and processing applications)

1. How can we (cost, power, scalability) and effectively (communication range, data latency, data interoperability) store and process data for developing monitoring of row crop diseases and precision application interfaces?

2. How can we (cost, power, scalability) and effectively (communication range, data latency, data interoperability) store and process data for developing autonomous (smart irrigation, smart fertilization & Farm machinery navigation) alert application interfaces?

APPENDIX B. DATA SETS- IOT SENSORS & THINGS BOARD

The real time performance data sets used to perform the analysis in section 4.6, 4.6.1 & 4.6.2 is attached herewith the link provided.

https://app.box.com/s/lqa6saevky3hq2y7k0jl5lxhty2ehm5m

The Things board open-source cloud rule chain.
ThingsBoard PE | Device group (purdue.edu)

APPENDIX C. ANOVA RESULTS

ANOVA
(pg. 129)

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	0.93	0.2324	1243.414439	0
Residual	2499	0.467	0.000187		
Total	2503	1.40			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	3.345356837	0.008099844	413.0149609	0
Communication Range (CR)- meters	0.000152889	9.77455E-06	15.64159128	1.10028E-52
Received Signal Strength Index (RSSI)	0.000157345	4.23919E-05	3.711676929	0.000210387
Signal to Noise Ratio (SNR)	5.0342E-05	0.000111712	0.450639427	0.65228854
Data Rate (DR)- bits/sec	0.055938895	0.000884811	63.22126062	0

ANOVA
(pg. 131)

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.077597665	0.077598	191.4184233	5.27238E-42
Residual	2502	1.014266832	0.000405		
Total	2503	1.091864497			

	Coefficients	Standard Error	t Stat	P-value
Intercept	3.649887257	0.04957527	73.62314	0
Communication Range (CR)- meters	-8.88425E-05	6.12822E-05	-1.44973	0.147260047
Received Signal Strength Index (RSSI)	-0.000575838	9.5921E-05	-6.00325	2.21529E-09
Signal to Noise Ratio (SNR)	-0.000117519	0.000219135	-0.53629	0.591809116
Data Rate (DR)-bits/sec	-0.009969401	0.004379682	-2.27628	0.022913258