Opportunities in Farming Research from an Operations Management Perspective

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Abstract

We review and analyze the farming (upstream agribusiness supply chain) research literature since 1965 to identify farming research opportunities for operations management (OM) researchers. A majority of reviewed papers in our corpus, until the turn of the 21st century, primarily focus on improving operational efficiency and effectiveness of farming using optimization techniques. However, during the last two decades, farmers' welfare and the interests of other stakeholders have drawn OM researchers' attention. This expanded focus on farming research has become possible due to the proliferation of mobile communication devices and the Internet, as well as advancements in information technology platforms and social media. Our review also shows that there is a paucity of OM literature that leverages increased data availability from the emergence of precision agriculture and blockchain to address major challenges for the farming sector emanating from climate change, natural disasters, food security, and sustainable and equitable agriculture, among others. Big data, in conjunction with opportunities for field-based experimentation, artificial intelligence and machine learning, and integration of predictive and prescriptive analytics, can be leveraged by OM scholars engaged in farming research. We zero in on specific questions, issues, and opportunities for research in farming.

Keywords: Farming, Predictive & Prescriptive Analytics, Data-driven, Agribusiness, Precision Agriculture, Blockchain

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1. Introduction

The motivation for this paper is grounded in the importance of farming as an important sector of the economy in all countries. The United Nations has articulated Sustainable Development Goal 2 as "End hunger, achieve food security and improved nutrition and promote sustainable agriculture [...] These worrying trends coincide with the diminishing availability of land; increasing soil and biodiversity degradation; and more frequent and severe weather events. The impact of climate change on agriculture compounds the situation." Thus, the agribusiness sector is expected to face daunting challenges in the upcoming decades that include but are not limited to climate change, food security, disruptions from sustained or erratic shifting patterns of floods and famine in agricultural regions, forest fires, and other natural disasters. Additional challenges will emanate from ever-increasing demand due to the growth in global population, notwithstanding shifts in consumption away from meat-based protein to plant-based protein, largely to alleviate the environmental burden imposed by the animal husbandry industry (Aschemann-Witzel et al. 2021). Advancing equitable and sustainable agriculture, while also warding off any regional geo-political and social conflicts arising from disputes associated with securing the availability of water, energy, and land resources for agriculture, will pose major challenges (Serraj and Pingali 2018, Basso and Antle 2020). These challenges will shape future operations management (OM) research to leverage technology advances and facilitate more transparent, timely, dynamic, and targeted decision-making for various stakeholders in the agribusiness sector.

Increased digital connectivity and emerging technologies will create data-rich environments for facilitating future OM research on farm operations. Major sources of data in this environment will include satellite-based remote sensing data, secondary data collected by governmental agencies, big data on soil and crop characteristics via precision agriculture, crop imaging data through the use of drones, weather data, social media data, data gathered via information technology platforms, and transaction data in value chains through blockchain technology. Big data, in conjunction with opportunities for field-based experimentation, can be leveraged by OM scholars in using both predictive and prescriptive analytics in an integrated manner to address major challenges for this sector.

All these factors motivated us to review research in agribusiness. Agribusiness is a vast topic of study that includes farming, processing of produce, and distributing to the end consumer. However, the scope of this paper is limited to farming operations - the upstream end of the agribusiness supply chain - due to space constraints. Our study primarily focuses on farm produce, but we also briefly discuss forest planning, planting, and harvesting of timber primarily to keep this area under the radar of POM researchers.

OM researchers are the primary audience of this paper. Therefore, we review published literature and provide directions to OM researchers for future research opportunities in farming. We searched for the relevant papers in operations management (OM) and related journals, and a recently published book, "Agricultural Supply Chain Management Research Operations and Analytics in Planting, Selling, and Government Interventions", edited by Boyabatli, Kazaz, and Tang (2022). We found 298 papers, whose details are given in

Endnote[1]. The farming-related research in OM has gone through an evolutionary process during the last six decades in terms of topical and methodological coverage. Until the end of the last century, the primary focus of OM farming research was to improve operational efficiency and efficacy. However, at the turn of the century, the research landscape started changing with increased focus on stakeholder management that also entails farmer welfare and sustainability issues while recognizing the opportunity to leverage the Internet and proliferation of mobile communication devices to empower marginal farmers[2]. The launch of e-Choupal by ITC Limited is a good example of the earliest intervention envisioned two decades ago to develop a rural digital infrastructure in India to create an e-marketplace to empower the farmers (Annamalai and Rao 2007, Chen et al. 2013). In the ensuing years, researchers also realized the potential for the enhanced role of emerging technologies, precision farming, new data collection and sharing techniques, and artificial intelligence and machine learning to address major challenges for agriculture (Spanaki et al. 2021, Rejeb et al. 2022). Issues related to Internet of Things (IoT), satellite imagery, drone imaging, blockchain, risk assessment, sustainability concerns, and government intervention in the presence of strategic farmers and cooperatives also emerged in the farming-research portfolio (Mondal et al. 2019, Pranto et al. 2021, Zhang et al. 2021).

The remainder of this paper is divided into four sections. In Section 2, we present an evolution of farming research. Section 3 discusses the 'Stakeholder Engagement for Farming in a Digital Era'. 'Operational Efficiency' is discussed in Section 4. At the end of each sub-section in Sections 3 and 4, we also identify some specific opportunities for future research based on identified gaps in the literature. In section 5, the paper concludes by identifying and discussing emergent themes for future research that have not been addressed well in the extant literature.

2. Evolution of Farming Research

We group the farming literature into two major categories: "stakeholder engagement for farming in a digital era" and "operational efficiency in farming''. Figure 1 gives the road map of this paper and lists various functions covered in these two categories.

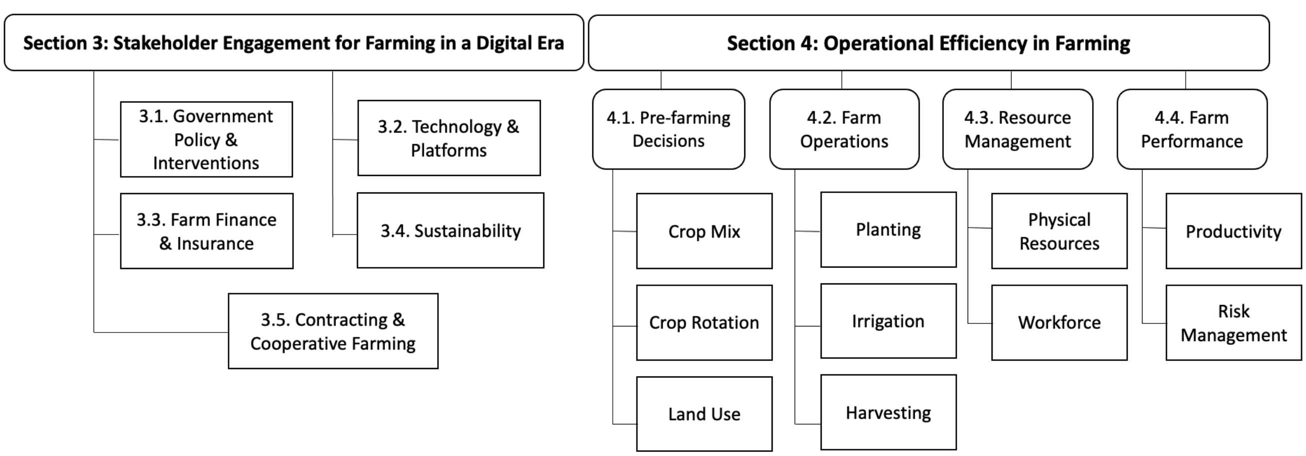

Figure 1: Road Map of the Paper

In this section, we provide the evolution of the research literature in farming. We searched for relevant research in operations management (OM) and related journals and selected 256 relevant papers (called corpus in this paper). Figure 2 shows the research growth using a 5-year moving average of the published papers spanning almost six decades, from 1965 to 2021. The growth rate is slow and steady, with an increase of about 0.62 paper per year over the last 15 years. However, this growth rate seems rather low for this sector of the economy. We hope this paper will open avenues for more research.

We also analyzed the evolution based on the following three criteria: purpose of analysis (predictive vs. prescriptive), analysis techniques, and type of data used. Overall, based on the corpus, prescriptive research (80.5%) attracted more attention from researchers than predictive research (19.5%). Figure 3 shows that prescriptive analytics always outnumbered predictive analytics. A possible reason for this may be the unavailability of data required for predictive analytics, discussed further in the rest of this manuscript. On the other hand, the figure also shows that the prescriptive curve has recently plateaued, indicating saturation of stand alone prescriptive analytics in farming operations. We believe that emerging OM research focused on prescriptive analytics in farming operations will increasingly involve integration with predictive analytics.

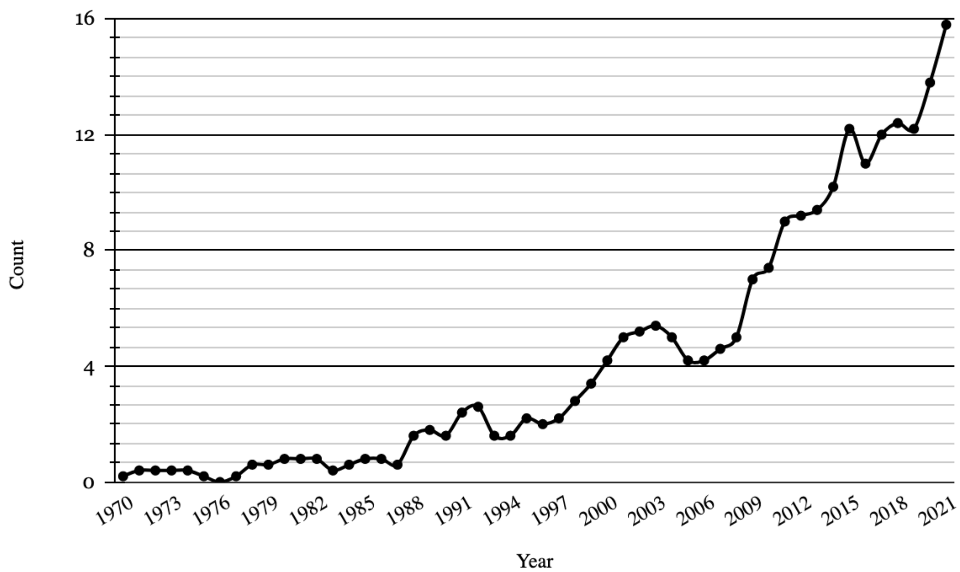

Figure 2: 5-Year Moving Average of Evolution of Upstream Agribusiness Research

From a data perspective, we use the commonly accepted categories of data type in OM research, which include: archival (secondary data), hypothetical (simulated), real (data for setting model parameters based on a real example or studying an actual event or case), and survey (primary). See for example, Gupta et al. (2016). A term of recent origin is “big data,” and we have added this term as another category. Figure 4 shows the growth of publications based on data type. Based on the corpus, papers most commonly used real data (41%), followed by hypothetical (24.6%), no data (20.7%), archival data (12.1%), survey data (1.2%), and big data (0.40%).

Figure 3: Growth of Publication Based on Purpose of Analysis

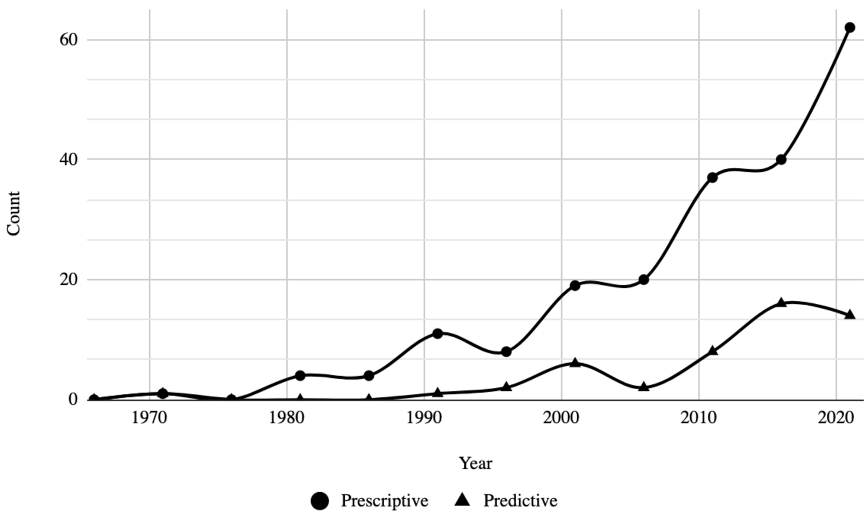

Figure 4: Growth of Publications Based on Data Type (Five-year Count)

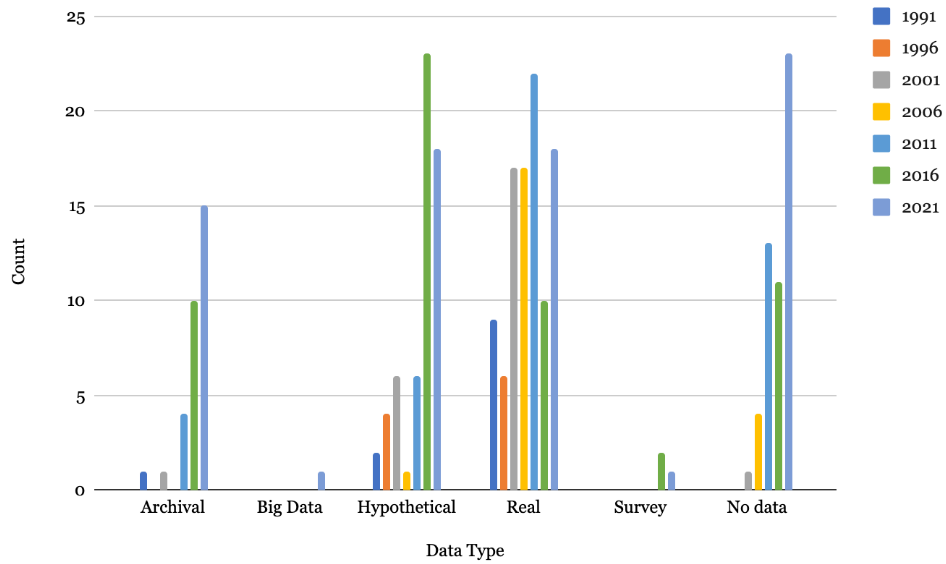

Table 1: Distribution of Papers for Purpose of Analysis, Data Type, and Analysis Technique Perspectives

	Purpose of Analysis		Data Type						Analysis Technique								
	Predictive	Prescriptive	Archival	Big Data	Hypothetical	Real	Survey	No data	AI/Machine Learning	Decision Analysis	Game Theory	Heuristics	Mathematical Prog.	Meta-Heuristics	Simulation	Statistical Analysis	**Total**
Stakeholder Engagement for Farming in a Digital Era	6.3%	19.9%	3.9%	0.0%	1.6%	7.8%	0.8%	12.1%	0.4%	2.0%	9.8%	0.0%	9.4%	0.0%	0.4%	4.3%	26.2%
Pre-Farming Decisions	1.6%	13.3%	0.8%	0.0%	3.5%	8.6%	0.0%	2.0%	0.0%	1.6%	0.0%	0.8%	10.2%	0.8%	1.2%	0.4%	14.8%
Farm Operations	5.1%	32.4%	2.7%	0.0%	14.5%	16.0%	0.4%	3.9%	0.0%	3.1%	0.0%	3.5%	23.4%	2.3%	1.6%	3.5%	37.5%
Resource Management	1.2%	10.2%	0.8%	0.0%	3.9%	5.1%	0.0%	1.6%	0.0%	1.6%	0.8%	0.4%	8.6%	0.0%	0.0%	0.0%	11.3%
Farm Performance	5.5%	4.7%	3.9%	0.4%	1.2%	3.5%	0.0%	1.2%	0.0%	1.6%	0.0%	0.0%	5.5%	0.0%	0.8%	2.3%	10.2%

An analysis of the techniques used shows that mathematical programming is used in the maximum number of papers (57.0%), followed by statistical analysis (10.5%), decision analysis (9.8%), game theory (10.5%), heuristics (4.7%), simulation (3.9%), meta-heuristics (3.1%), and artificial intelligence (AI) and machine learning (0.4 %). In Table 1, we further illustrate the distribution of papers mentioned in Figure 1 from the perspective of data type and analysis techniques.

In the next section, we provide an overview of the emerging farming-research era, wherein scholars have largely focused on understanding and influencing stakeholder interactions (e.g., the role of government intervention, contracting, and cooperatives) and leveraging technology and platforms to address challenges in the areas of finance, insurance, and sustainability to improve farmers' welfare.

3. Stakeholder Engagement for Farming in a Digital Era

Technological developments, concerns for farmers, focus on ending hunger, achieving food security, improved nutrition, and promoting sustainable agriculture are fueling the recent developments in agribusiness research. Several researchers have focused on understanding and shaping the role of government intervention and leveraging information technology and platforms to enhance farmers' welfare. Studies in loan and insurance management for farmers, as well as contracting between farmers and other stakeholders, have also been a significant area of research over the last decade. Increased attention to issues such as climate change, food security, and welfare of marginal farmers has also led to significant research on sustainable agriculture. In this section, we discuss these developments under the following five categories: (1) Government Policy and Interventions, (2) Technology and Platforms, (3) Farm Finance and Insurance, (4) Sustainability, and (5) Contracting and Cooperatives.

3.1. Government Policy and Interventions

Farming policies established by governments generally provide subsidies to supplement farmers' income, pricing to influence commodities' cost and supply, and guidelines on sharing information or managing information systems. The goals of these policies include maximizing farmers' profits and social welfare. The majority of papers (twenty papers) on this topic use prescriptive analytics, followed by predictive analytics (eight papers). Research focused on public policy and government intervention has started considering stakeholders to be strategic and hence relied predominantly on game-theoretic frameworks. Among prescriptive works, eleven papers have not used any data, and the rest have used real data. Among predictive ones, four studies utilize real data, and four use archival data.

The following studies investigate various policies using predictive analytics in conjunction with archival data. Amores and Contreras (2009) use data envelopment analysis to develop an allocation structure for government subsidies that improve the production quality and the environmental and social values of agriculture. Serra et al. (2014) consider a sample of arable crop farms in the Catalan region and propose farm-level technical and ecological efficiency measures that can account for the uncertain conditions faced during farm production.

Their findings indicate that technical efficiency is a little lower in adverse conditions than in the right growing conditions. They also find that nitrogen pollution can be substantially lower under good vis-à-vis terrible growing conditions. Minviel and De Witte (2017) use robust conditional frontier modeling along with nonparametric econometrics to estimate the influence of subsidies on farm efficiency. Their findings from using an unbalanced panel data from 313 French farms suggest that subsidies negatively affect farms' technical efficiency (i.e., efficient use of conventional inputs and outputs). Ayouba et al. (2019) introduce a price advantage measure as the difference among efficiency scores calculated with quantity-based and value-based data. This measure captures the increase in the farm's profit rate because of a favorable input and output price setting. They show the application of this measure using a French farm's dataset in the context of successive common agricultural policy reformations.

The following studies utilize real data in conjunction with predictive analytics. Sumpsi et al. (1997) use the data on family farms in Spain to study farmers' behavior to government policies. They find that the behavior of farmers (regarding cost minimization of working capital, hired labor, and risk) depends on multiple functions and cannot be explained by a simple objective function. Using a dataset from farm cooperatives in Japan, Sueyoshi (1999) investigates distribution functions of efficiency among two groups of farmers for new policies. To do so, he proposes a ranking system using data envelopment analysis (DEA) in conjunction with efficiency analysis and index measurement. Cherchye and Van Puyenbroeck (2007) use non-parametric DEA to estimate the profit when the government or policy-makers do not provide or share complete information on prices and technology used in different farms. They show the application of their technical contribution using German farm data, wherein the information on technology and prices are not complete. García-Alonso et al. (2010) use artificial neural network models to predict the gross margin of farms that can be used by governments to improve subsidy allocation. The authors examine the effectiveness of their approach vis-à-vis using multiple linear regression models.

Another stream of research employs prescriptive analytics using no data. Cabrini et al. (2004) utilize portfolio theory in conjunction with nonlinear integer programming to identify an efficient combination of specific advice to farmers on how to market their products and support them in their attempts to manage price risk. Tang et al. (2015) examine whether farmers should directly use information (e.g., market information) to improve their production plans or adopt agricultural advice from the government or non-governmental organizations (NGOs) to enhance their operations. They model this interaction with a Cournot competition for two farmers under uncertain market demand and process yield. Their result shows that in equilibrium, farmers use market information to increase their profits. In a follow-up paper, Chen and Tang (2015) investigate whether the above information creates economic value for farmers. By analyzing a similar Cournot competition game, they show that private signals produce value by increasing farmers' welfare. Nevertheless, this value declines as the public signal becomes available. Liao and Chen (2017) consider a problem wherein they study asymmetric information structures of farmers' information management and utilization instead of focusing on private and public information. They assume that farmers obtain information indirectly from local social networks or directly from the government or NGOs. Hence, they may have very different information channels. The results of Liao and Chen's (2017) game theoretic model show that a farmer may be more (less) productive when seeing a negative (positive) signal, and she may benefit from the improvement of a signal she cannot see. Additionally, the farmer may become worse off when another farmer provides a signal to her. He et al. (2018) study a Cournot model under asymmetric market information and examine the formation of informational coalitions between farmers. Their findings provide guidance on how farmers' efforts link farmers in developing countries by integrating market information. Their results indicate that the government or NGO should give the right amount of market information to the right farmer, and providing too much information leads to more ineffective production.

Liao et al. (2019) examine the effect of information provision policies on farmer welfare in developing economies wherein producers lack appropriate and timely information for decision-making about their production strategies and marketing. When market information is given free of charge, their results show that giving information is always helpful to farmers at the individual level. However, giving information to all farmers may not be welfare-maximizing for all farmers. Jiang et al. (2021) analyze the effectiveness of two government subsidy programs designed for farmers producing bioenergy to increase their supply for sale to a power plant. The subsidy programs include schemes, wherein farmers are offered subsidies a) based on quantity of bioenergy; b) to cover losses when market price for bioenergy falls below a trigger price. Chintapalli and Tang (2021a and 2021b) investigate the effectiveness of credit-based minimum support prices (MSP) wherein the government credits risk-averse farmers, in case the prevailing market price were to fall below the stated MSP. In Chintapalli and Tang (2021a), the authors analyze the impact on both net benefit to farmers and net social value after accounting for the cost of implementing MSP. In Chintapalli and Tang (2021b), the authors analyze the impact of cost subsidy and MSP on net benefit to farmers and net surplus. Ye et al. (2021) analyze the impact of a farmer subsidy program vis-à-vis a producer subsidy program in a setting wherein risk-averse farmers with limited land capacity and yield uncertainty produce biomass feedstock to supply to a bioenergy producer. The strategic interaction between the government, farmer, and producer of bioenergy is analyzed while also considering subsidy budget constraints and environmental benefits. Guda and Dawande (2021) develop a model to evaluate the efficacy of guaranteed support price schemes offered in developing countries to small farmers and underprivileged consumer populations. They analyze a Stackelberg game between a social planner and small farmers while incorporating the strategic behavior of the farmers and the consuming population that falls into two categories, i.e., above and below the poverty line.

Another body of prescriptive analytics utilizes real data. Wade and Heady (1978) study a governmental agency that evaluates multiple alternative sediment control policies to provide optimal planning on technical, regional, and cost distributions of agricultural production. Their results support decision-makers to form national sediment control plans. Focusing on pricing and related policies, Baum et al. (1984) introduce a joint application of optimization and simulation methods to develop a recursive programming model that considers the uncertainty of market prices and government policies in managing production strategies and decision-making in farms. They assess their model's quality by running two simulations with stochastic commodity prices and yields for a Texas farm and provide credible and different results for the various economic environments. Owsiński and Romanowicz (1985) develop a linear programming model and use sensitivity analysis to examine the rationalization of agriculture policies in a country and its impact on pricing the commodities. Their mathematical contributions provide guidance on excluding the impacts of specific parameters on some variables in the sensitivity analysis. Önal (1988) uses a mathematical model to investigate the social and economic results of government intervention policies (i.e., pricing and allocation of resources) in agriculture. The result shows that various support policies lead to welfare transfers among the business environment participants, keeping the sectoral production and overall social welfare almost unchanged. Their findings also explain that for a cogent allocation of scarce resources, specific weight should be given to those proposals supporting farmgate demand for increasing agricultural incomes and the agribusiness contribution to the national economy. Önal et al. (1995) examine the effect of increasing government subsidies for small farmers on their farm productivity and income distribution. Their mathematical model results show that a significant increase could be created in farmers' performance (i.e., growth in their output) and welfare distribution (i.e., equity) by reallocating subsidized government credits (i.e., agricultural loans at a subsidized rate). Teich et al. (1995) consider a negotiation between the government and the agriculture union to deal with income policy for Finland's agriculture industry. Their decision support system provides guidance on how meditation techniques can help structure the preferences and pricing policies and find an agreement for a negotiation problem. Sueyoshi et al. (1998) employ data envelopment analysis to propose a new approach for bilateral performance comparison of farming cooperatives using production and cost features. Using a dataset from farm cooperatives in Japan, they perform a bilateral performance comparison to provide policy-makers a basis to reorganize the Japanese agriculture industry. Alizamir et al. (2019) use game theory to examine (1) market price drops below a specific price (i.e., to offer price loss coverage) and (2) when farmers' revenue falls below a threshold (i.e., to provide agriculture risk coverage). The authors find that the first subsidy policy always prompts farmers to plant more plots (i.e., pieces of land, lots). However, farmers may plant fewer plots under the second subsidy policy, driving a lower crop supply. Both farmers and consumers may be better off under price loss coverage for an extensive range of parameter values, even when the reference price depicts the past average market price. They confirm with the data that their guidelines are backed by farmers' enrollment statistics for each subsidy program. Akkaya et al. (2021) examine the impact of policy instruments of taxes and subsidies on the adoption of innovative production methods in agribusiness, wherein there is significant uncertainty faced with the adoption of the innovative method that also entails learning-by-doing. The authors consider a setting wherein an agribusiness has access to both traditional and innovative methods and consumers have a higher valuation for the output using the new and innovative method. In the next section, we present papers on the technology and platforms.

Judicious adoption of agricultural innovation can benefit farmers by enhancing their productivity; lowering their environmental impact; and handling the challenges related to soil, weather, and market requirements. Fostering innovation usually demands the government set policies that incentivize farmers to experiment with new technologies and practices. Further research is needed to understand the determinants of farmers' willingness to experiment with the adoption of specific agricultural innovation in a dynamic setting where communication among farmers may result in farmers' learning from each other. This in turn can inform the government in a timely manner to make any changes in their policy required to achieve the desired impact.

3.2. Technology and Platforms

The emerging era is witnessing enhanced use of technology, precision farming, and IT platforms facilitated by new data collection and sharing techniques (e.g., Chen et al. 2015, Zhou et al. 2020). While satellite imaging for agriculture has been prevalent over several decades, Internet of Things (IoT), drone imaging, and blockchain are beginning to permeate farming operations. Over the upcoming decade, big data is expected to lead to better predictive and prescriptive modeling in support of farm operations, resource management, and other critical functions that support farming. Since the advent of the 21st century, farmers' welfare has moved towards taking the center stage amongst stakeholders in agribusiness, in both developing and developed economies. e-Choupal is a good early example of the impact of technology on the benefit of farmers in a developing economy. e-Choupal in India is an initiative of ITC Limited that provides real-time information to farmers to align their farm output with market demand. This also helps ITC in its procurement activities. Developments in information technology are helping farmers to get information about price shifts, changing weather patterns, crop production techniques, and new practices to produce crops. We find nine papers in the literature that are related to information technology. Four of these studies use predictive analytics, and five papers use prescriptive analytics.

We first present studies using predictive analytics. Aubert et al. (2012), based on survey data, develop a model explaining the difficulties in adopting precision agriculture technology. They utilize technology acceptance and diffusion of innovation theories. Their empirical analysis employs survey data from farms in Canada. Their findings emphasize the value of compatibility among precision agriculture technology elements (such as ease of use, observability, perceived resources, and perceived usefulness) and the central role of farmers' expertise. Two papers used archival data with a focus on predictive analytics. Parker et al. (2016) show that, in addition to improving market efficiency, timely and reliable information acquired through information and communication technologies decreases the geographic price dispersion of crops and also the rate at which prices converge. They utilize a data set from a text message service in India that gives daily price information to market partners. Petridis et al. (2020) determine factors that influence the ability of firms to innovate or imitate in agribusiness using information technologies. They find that innovation is positively correlated with income, female employment, export practices, and the level of training of farmers. In contrast, imitation is improved in nations whose cultures are distinguished by uncertainty avoidance.

We next focus on studies using prescriptive analytics. Using prescriptive analysis with hypothetical data, Zhang and Goddard (2007) develop a Web-based Decision Support System (DSS) wherein a layered software structure helps design the Web-based DSS, and a component-based framework executes the Web-based DSS in a distributed environment. They apply this Web-based DSS to the National Agricultural System. For example, this system develops an index indicating the moisture departure for a region, executing a simple supply-and-demand model for a water balance equation.

The following three studies use prescriptive analytics with no data. Lowe and Preckel (2004) discuss the challenges in agriculture and farming and see a need for efficiency and modern decision technology tools (such as computers and sensor technology). They propose some new and significant issues such as product proliferation and precision production facing the industry that could be resolved by new technology. Chen et al. (2013) develop a game theoretic model to study the ITC's network platform for farmers in India. They examine ITC's incentive for farmers, which is trading the products directly to ITC at the market price in the regional market, and investigate the farmers' strategic quantity decisions. They find that the implicit agreement functions as a formal contract, despite the price elasticity of the regional market. Chen et al. (2015) develop a stylized model to study the peer-to-peer interactions among farmers when both knowledge learning and sharing are possible through online forums. An expert constantly watches the platform and answers the farmers' questions but may be non-responsive sometimes due to the limited capacity. Their results show that employing more workers to monitor the platform regularly damages peer-to-peer cooperation. Kurkalova and Carter (2017) employ the resource-based view to evaluate a specific green technology (i.e., yield monitors to reduce the use of liquefied petroleum as a source of energy) using a five-step simulation modeling approach to estimate the benefits of this technology represented as dollars saved and decreased greenhouse gas emissions in agriculture businesses. Zhou et al. (2021) analyze an asymmetric two-stage game to understand whether a wider dissemination of market information, facilitated by government and non-governmental organizations in developing countries, is always beneficial to farmers. They find that optimal information dissemination policy depends on the nature of competition, uncertainty in yield, source of funding, and the overarching goal of the social planner.

While recent research provides a foundational start, there is a need for future research in OM to develop economic models that can offer more targeted insights for farmers by capturing the strategic interactions between farmers, buyers, platform providers, and government interventions in an increasingly transparent and data-rich environment facilitated by precision technologies and platforms. There is a need to understand what would drive the adoption of a specific portfolio of precision agriculture technologies by farmers in their operations and facilitate farmers' requisite engagement with platforms, particularly for marginal and small farmers in developing or underdeveloped countries. Empirical research can help estimate the impact of the adoption of precision agriculture technologies, information technologies, and platforms on metrics of interest to stakeholders.

3.3. Farm Finance and Insurance

Farm finance papers focus on investment in farm resources, crowdfunding, factors affecting the return on investment, and farmers' income using empirical as well as mathematical models. Scholars use predictive analytics (in two papers) and prescriptive analytics (in six papers) to examine these topics. Data sources for these studies include archival data (one paper), real data (three papers), no data (four papers), and primary data (one paper).

Among studies that use predictive analytics, Martins and Lucato (2018) examine the effect of the production factors, and their empirical analysis of 152 agriculture cooperatives shows no significant correlations between the production structures and the financial performance of cooperatives. da Silva et al. (2020) develop a two-part fractional regression model with conditional free disposal hull efficiency (i.e., a non-parametric method to measure the efficiency of production) responses to support two-stage regression analysis. Output is gross income, and inputs are land and labor expenses and other technological inputs.

Papers undertaking prescriptive analytics using real data include Colin (2009), Heikkinen and Pietola (2009), and Viaggi et al. (2010). Colin (2009) develops a simulation for a financial valuation model to study the impact of the acceleration of the sugarcane factory implementation on the value of the sugarcane agro-industrial complex. Heikkinen and Pietola (2009) develop a dynamic stochastic programming model for a Finnish farm to find the optimal investment in crop production. They consider the loss due to income uncertainty for each period. Viaggi et al. (2010) use an integer programming model to simulate investment management in various policy and price scenarios, focusing on the decoupling of the Common Agricultural Policy (CAP). Their multi-objective farm-household dynamic integer programming model considers the features of individual assets, including aging and persistence, through the explicit consideration of transaction costs.

The following four papers perform prescriptive analytics without using any data. Zhou et al. (2020) examine how crowdfunding, the practice of funding a project or venture by raising many small amounts of money from a large number of people, can help poor farmers. Their result, derived from a game-theoretic model, shows that the optimal choice depends on the interplay between the customer’s willingness to pay and the cost coefficient for a quality investment. Using a Markov decision process, Qian and Olsen (2020) examine the coordination of operational and financial choices of agricultural cooperatives. In this model, producers’ equity is expected to be in proportion to their crop supplied. They characterize the optimal solution and provide insights into how the co-ops manage the risk and cash position.

Insurance mitigates the risk of lending to the farmers and enables repayment of loans, lessens budget variations of expenditures by shifting climatic risk to the private sector, raises fiscal period during shock cycles, and helps maintain agriculture growth, which likely provides job creation. Assa et al. (2021) propose a revenue insurance policy that can increase investment in agriculture and also be a substitute for government subsidies. They use total profit (Pareto optimal) and the Stackelberg game to show the impact of commodity price insurance on risk management and find that insurance will enhance the impact of the investment. Yi et al. (2021) compare financing options for a cash-constrained farmer using mathematical programming. They find that the presence of an intermediary finance platform has a positive impact on the welfare of the farmer and the total profit of the supply chain.

There is a significant opportunity to understand the interplay between financial decisions and equity redemption for marginal and small farmers in a cooperative. Receiving a loan can be difficult because co-op members' equity is not static and guaranteed; defaulting on a loan could also make this problem more serious. Also, governments have indicated that activities that do not deliver punctual redemption of previous equity are unfair. Researchers are encouraged to investigate how constraining the liquidity condition on loan repayment, and equity redemption may impact the operational and financial decisions within proportional investment cooperatives, wherein a farmer's equity is based on the amount produced at a farm. In the next section, we present papers on sustainability in farming.

3.4. Sustainability

Farming operations impact the natural environment as well as societal aspects. Ecological considerations include building and maintaining healthy soil; managing the water system; decreasing air, water, and climate pollution; and promoting biodiversity (Dalsgaard et al. 1995, and Darnhofer et al. 2010). From the social aspect, farms and agribusinesses need to plan to manage and improve health and social equity, human rights, labor rights, working conditions, social responsibility and justice, community well-being, and resilience (Bacon et al. 2012). We find five papers that use prescriptive analytics with no data, or with hypothetical and real data. Two papers utilize predictive analytics in conjunction with archival data, with a focus on the environmental issues or the issues at the environment-economic interface.

Using prescriptive analytics with no data, Hosseini-Motlagh et al. (2020) utilize an evolutionary game to study the behavior of financially constrained farmers who receive financial support from a distributor, based on their sustainability and investment decisions. They study how farmers strategically make decisions regarding environmental issues (i.e., emission reduction) considering the time value of money. They find that providing financial support to promote sustainability leads to a win-win situation for farmers and a distributor. Generally, financial support for sustainability improves the farm's environmental sustainability and the demand for the farm's output, while it supports financially weak farmers to remain in the market and enjoy higher social welfare.

The following two papers employ hypothetical data in conjunction with prescriptive analytics. Prabodanie et al. (2014) consider the tradable nitrate permit market for farmers and investigate a set of alternative linear programming models to find optimal permit prices in advance. They find the market price structures for different environmental conditions and obtain the physical and economic conditions required to assure consistent prices. Wang et al. (2020) develop a Quality Improvement Activities (QIA) framework to study the tradeoffs between carbon emission, quality, and time in perishable food production. Their multi-objective optimization model generates the three-dimensional Pareto front to facilitate decision-making. Their results show that farmers can mitigate quality uncertainty but cannot change the farm's random nature. Randomness here refers to the amount of random time needed to process a task on a farm and the amount of carbon emission created.

The following two papers utilize real data to run their prescriptive analytics. Elfkih et al. (2009) use goal programming to examine sustainability issues of irrigated agriculture. The motivation for this research comes from the European "Water Framework Directive." They observe that solutions acceptable for environmental sustainability do not seem reasonable for profitability, and vice versa. Thus, they suggest looking for best-compromise solutions among the solutions to design sustainable cropping patterns. dos Santos et al. (2010) study a farm production problem wherein they must meet the demand and optimize both the division of areas in plots and crop rotation plan while considering ecological constraints. The ecological constraints include the interdiction of particular crop sequences and the regular insertion of manures. Their proposed linear formulation helps farmers to maximize land occupation while considering the ecological constraints.

Gomes et al. (2009) and Picazo-Tadeo et al. (2012) use archival data for predictive analytics. Focusing on a group of farmers in the Brazilian Amazon and using DEA models, Gomes et al. (2009) examine the sustainability performance of those farms. They find that the maintenance of production systems to keep the efficiency of both cultivation processes and labor at a high level is the primary factor in agricultural sustainability. Picazo-Tadeo et al. (2012) assess the ecological performance of Spanish olive-growing farms using directional distance functions and data envelopment analysis. In the next section, we present papers on contracting and cooperative farming.

Future research can focus on leveraging big data and integrating predictive analytics with prescriptive analytics to enable targeted government subsidies and other interventions to minimize the impact of agricultural runoff of pesticides and fertilizers into lakes, streams, and groundwater. As one examines past research focused on sustainability in agriculture, it is also clear that OM research in agriculture needs to pivot considerably towards enabling the achievement of the United Nations' Sustainable Development Goals set up in 2015. Studies on the social or socio-economic aspects of sustainable farming are significantly lacking in OM literature. Topics such as agricultural and labor management, education and housing conditions for the workforce, safety and health hazards caused by pesticide spraying for the farm workforce, and improvement of rural areas around farms and their community are emerging topics in other management fields. One needs to utilize the data at the farm level or within co-ops to investigate mentioned social aspects of sustainability in future research.

3.5. Contracting and Cooperative Farming

Contracts between farmers and buyers are established to guarantee fair compensation for farmers while ensuring the supply of products with specified characteristics is delivered on time to the buyers. Seven papers in this section use prescriptive analytics while using no data, whereas only one paper uses predictive analytics in conjunction with archival data. We divide papers into two categories: papers focusing on contracting features and those focusing on contracts for cooperative farming.

We first present the contracting papers that focus on prescriptive analytics. Ryan (1999) models a bargaining scenario between a farmer and a landowner, wherein any agreed production plans and weather forecasts play an intervening role. Results show that the two players may agree on the details of contingent production plans, contingent resource evaluations, and weather forecasts to enhance profits not only relative to those plans but also in a manner relative to each other. Burer et al. (2009) investigate contracts with specific bonus and penalty features in the seed industry. By considering the assumption of uniform demand, they fully characterize all coordinating contracts. Niu et al. (2016) consider firm–farmer and firm–cooperative–farmer channel structures to examine how each contract type affects the coordination of efforts and utilities by members in the channel. They consider wholesale price and cost-sharing contracts for the firm–farmer channel and observe that the latter can result in a win-win result for both the farmer and the firm when the firm's cost-sharing is lower than a threshold level. Further, they investigate the firm–cooperative–farmer structure using two bargaining models based on the cooperative's commission contracts with the farmer. Hu et al. (2019) study how strategic and naive farmers with different production costs, under price variations, make crop planting decisions to maximize their welfare. Their equilibrium results show that naive farmers' decisions may create recurring overproduction or underproduction, causing price volatility. Federgruen et al. (2019) study a Stackelberg game wherein a manufacturer (leader) chooses a set of farmers to extend a menu of contracts, and each farmer (followers) picks a contract from this menu in advance of the growing season. They find that when finalizing the contract menu, the manufacturer can limit the option to relatively simple menus, depending on the farmer pool's heterogeneity. Rajput and Venkataraman (2021) develop a Stackelberg game between a firm and a farmer and propose a pricing mechanism that adjusts the market price to accommodate extreme price fluctuations that can enable both parties to avoid violation of the contract. Ayvaz-Çavdaroğlu et al. (2021) analyze policies for a for-profit cooperative that offers quality-based payments to risk-averse farmers who operate under yield uncertainty, quality requirements, and open market prices. They find that farmers consistently underinvest in crop quality when the quality-based incentive payments mimic open market prices. They propose easy-to-implement policies that can lead to gains for farmers when used in conjunction with crop insurance. Chen and Chen (2021) study the impact of contracting between the buyer and farmers in developing economies, wherein the buyer firm commits to an ex-ante procurement price and promises to buy the high-value agricultural product. The analysis focuses on the buyer's cost reduction efforts and its impact on suppliers' participation and economic benefit for contract farmers vis-à-vis non-contract farmers.

We found only one paper that uses predictive analytics. Puchalsky et al. (2018) examine the problem of price variations and their impact on contract farming. Their models predict variations in the price of products and services for farmers. They use five optimization techniques (i.e., Differential Evolution (DE), Artificial Bee

Colony (ABC), Glowworm (GSO), Gravitational Search (GSA), and Imperialist Competitive (ICA)) to achieve the best time-series forecast for prices.

The next topic in this section covers cooperative farming, wherein three papers use prescriptive analytics with no data. Palsule-Desai (2015) studies the competition between fringe farmers and a two-tier cooperative network (i.e., contract farmers and a coordinator). The author investigates the coordinator and profit-sharing roles in allocating costs/benefits of externalities in improving network performance, using a non-cooperative game theory framework. An et al. (2015) study five game-theoretic models to investigate the effect of formal or informal co-ops on reducing production cost, increasing/stabilizing process yield, increasing brand awareness, eliminating unnecessary intermediaries, and eliminating price uncertainty. Considering pricing concerns in farming, Tang et al. (2016) study contracts with partially-guaranteed prices between farmers and agri-food companies (i.e., buying firms). In their Stackelberg game (i.e., leader-follower game), the buying firm (leader) commits to purchase the product when harvested, offers a guaranteed unit price for any specific portion of the product, and consequently provides the market price prevailing upon delivery for the remainder. Then, the farmer (follower) chooses that particular portion. They characterize the optimal solution under various conditions, such as when the purchased quantity is exogenous or endogenous and when the buying firm provides advisory services to the farmer. Lastly, Shi et al. (2019) consider the storable agricultural product inventory problems for farmer cooperatives by examining a class of stochastic and dynamic inventory models with randomly varying but known supply and price. They characterize the optimal selling policies to maximize the farmer cooperatives' expected profit under various cost functions. Using prescriptive analytics by utilizing hypothetical data, Qian (2021) proposes a two-stage model of a cash-constrained farmer who has the option to convert a raw commodity into a value-added product by joining an agricultural cooperative. As the cooperative is a closed membership, the farmer has to decide whether to join it or not and if one opts to join then decide the production capacity and equity investment.

There are several avenues for future research in this area. One can utilize data collected from farms/co-ops to determine or predict the pre-planting fixed buying price (or formula) for crops in contracts, design a repeated contract based on the timing of planting/harvesting seasons, develop contract terms based on the prediction of environmental (weather, soil humidity, etc.) and local/international political issues. Further, one could investigate how the buyers can use contract farming to create farmer pools and thus aggregate the input procurement, services, and labor requirements.

In the next section, we discuss the literature on "Operational Efficiency in Farming". While research in the emerging era has largely focused on understanding and influencing stakeholder interactions, leveraging technology platforms, and sustainability to improve farmers' welfare; the issues of concern in traditional era research have been predominantly on facilitating decision-making for improving performance in farm operations, albeit being largely devoid of leveraging field-data.

4. Operational Efficiency in Farming

The research focusing on improving operational efficiency in farming includes both predictive and prescriptive techniques. We discuss this research in the following four groups: (1) Pre-farming Decisions (crop mix, crop rotation, and land use), (2) Farm Operations (sowing/planting, irrigating, and harvesting), (3) Resource Management (farm inputs [fertilizers, manure, seeds, pesticides], farm machinery, and workforce), and (4) Farm Performance (productivity and risk management). The details of the papers on operational efficiency in farming are included in Table E1 in the E-Supplement. The table summarizes each paper's data type, analysis technique, and source title. In the following subsections, in addition to presenting the broad research areas in each group, we discuss how recent technological development may introduce new research opportunities.

4.1. Pre-Farming Decisions

Pre-farming decisions are made before sowing starts. We include crop mix, crop rotation, and land use in this category as described below.

Crop Mix: Crop mix specifies the proportion of different types of crops to be planted on a given land to maximize revenue/profit. Factors that influence crop mix decisions include land productivity, soil type, and yield response to fertilizer/pesticide applications (Rădulescu et al., 2014).

Crop Rotation: Crop rotation identifies the sequence of different crops to be planted in a field over several planting cycles. Rotation helps in maintaining soil health, reduces dependence on synthetic fertilizers and nutrients, and helps in maintaining environmental sustainability.

Land Use: Land is one of the most important resources in farming, directly contributing to overall farm output. Farmers need to decide on land use, based on the season and demand-expectation, the type of crops to grow to get maximum return on assets. Land-use decisions also include considerations for factors such as farm inputs and sustainability, which have a direct impact on soil health and thus on present and future crop yield from the farm. The proportion of land allocated to different crops is important for maintaining soil health, improving crop productivity and yield, and the operational profitability.

We list all the papers in the above sub-categories in Table E1 in the E-supplement. We give below an overview of the models and techniques used in pre-farming decisions, followed by future research directions.

Modeling approaches have analyzed pre-farming decisions in both deterministic and stochastic scenarios. The input parameters include market price (forecast), market demand, yield, irrigation availability, etc. Pre-farming decisions are influenced by crop life, farm size, government subsidies, and minimum support prices. There is scope for frequent decision making in medium- to short-life crops such as wheat, rice, or many horticulture crops. The large farms may be more amenable to also investing in technology infrastructure that uses scientific decision making to optimize yield or profits whereas small farms (less than 5 hectares) are not able to realize the benefits of such approaches. Government subsidies and minimum support prices for selected crops also influence farmers' decisions about the type of crop to be planted.

Technological developments are going to influence pre-farming decisions. With the increase in social-media networks, farmers are exposed to larger peer-discussion and advisory groups that influence pre-farming decisions. Future research can estimate drivers of the diffusion of social media interactions among farmers and examine its influence on their pre-farming decisions and ensuing performance. There is also a rise in the amount of data available through satellites, drones, and the Internet of Things. This data can be analyzed using artificial intelligence and machine learning for better pre-farming decisions. Advances in machine learning can be used to estimate the impact of pre-farming decisions on yields and other economic and environmental metrics for the farm. For example, in a study supported by the World Bank, Deininger et al. (2020) use machine learning to analyze the crop and yield data collected using satellites, to examine the impact of crop rotation on yields and the ensuing financial performance of farms in Ukraine. With the advent of precision farming, future research can engage in big data analytics to further analyze this impact by controlling for soil conditions, rainfall, temperature, application of fertilizer, irrigation, and timing of harvesting, among others. Similarly, with free Earth Observation (EO) data availability, scholars are now able to address questions that they were not able to before. For example, by utilizing EO and geographic information system (GIS) data, Poortinga et al. (2020) run simulations to examine the effect of traditional drivers of change on land use and predict the chance of changes in different areas and how it may affect the agriculture and sustainability practices in those regions. Changes in climatic conditions too will behoove farmers to seriously examine their pre-farming decisions and look for less resource/water-intensive alternatives. For instance, there exist data on several factors including but not limited to land use and boundaries, forest cover, monitoring of environmental interactions, crop yield and production, etc (see https://www.nass.usda.gov/Research_and_Science/Cropland/sarsfaqs2.php). Understanding the impact of crop mix and crop rotation on yield and financial performance at farms under changing climatic conditions can also enable land use decisions, particularly when water resources become scarce.

The models proposed in pre-farming decisions are based on deterministic market conditions such as demand or price while broader but very relevant issues such as droughts, unemployment, currency fluctuations, diseases, etc. are not incorporated into the models (Brulard et al., 2019, Albornoz et al., 2020, Cervantes-Gaxiola et al., 2020). In addition, the present models are tested by either simulated data or limited real data from farms. There is a need to get larger volumes of quality data from multiple farms to build a realistic model that can be tested and used by farmers (Ridier et al., 2016, Brulard et al., 2019). Thus, models developed in the literature have severe limitations in terms of lack of real-life application and thus farmers' confidence in these models (Brulard et al., 2019). Emerging technologies, such as 4G/5G-enabled smartphones, water and soil sensors, drones, and satellites, may be able to provide farm-level data to facilitate pre-farming decisions for small and marginal farmers that consider terrain, soil, weather, climatic, and economic conditions in the region. Next, we briefly introduce the body of the literature on farm operations.

4.2. Farm Operations

Planting, irrigation, and harvesting activities constitute the bulk of what has been termed farm operations in this paper. We describe them below and list the relevant papers for each activity in Table E1 in the E-supplement.

Planting: Planting activities focus on scheduling of tilling of lands, plowing, and planting of seeds and saplings. See for example Wijngaard (1988) and Aliano Filho et al. (2019).

Irrigation: Irrigation research focuses on irrigation strategies, policies, and network design. Irrigation has a major influence on the final crop yield and it has a major environmental impact due to the usage of groundwater and as a medium for fertilizer runways, which pollute water bodies. Building dams and canals to support irrigation influences costs. Other infrastructure costs from an individual farmer's perspective include pipes, pumps, and fuel (electricity, diesel). Irrigation network design addresses questions about water distribution system and channels, irrigation pumping capacity, area to be irrigated, pump and machinery life, and maintenance situation (Gonçalves and Vaz Pato., 2000; Zhang et al., 2009; Gonçalves et al. 2014).

Harvesting: Harvesting includes identifying ripened/ready/mature crops and cutting/chopping/separating them from the origin. The nature of the crop, soil conditions, and terrain can impose special considerations for the planning and scheduling of harvesting. Planning for harvesting entails the allocation of specific time periods to harvest a section of the forest, farm, or orchard. The scheduling of harvesting periods is done in conjunction with the allocation of labor and equipment required for harvesting, loading of the harvest for transportation, and scheduling of transportation to post-processing facilities, markets, or storage facilities.

Timber harvesting, a major part of forest planning, considers the impact on wildlife habitat, among other considerations (Carvajal et al., 2013; Constantino and Martins, 2018). In the case of crops such as sugarcane, ensuring supply of the crop to the sugar mills requires coordination between scheduling harvesting in specific sections of each farm while simultaneously loading the sugarcane crop (also termed as harvest fronts) and transporting it to the sugar mill to meet its production needs in a timely manner (Álvarez-Miranda et al., 2018). Fruits and vegetables, due to their perishable nature, provide a distinct harvesting challenge wherein each type of produce has a different ripening curve (Escallón-Barrios et al., 2020; Gómez-Lagos et al., 2020). Hence, one has to schedule harvesting of these different types of produce in specific periods that match their corresponding ripening characteristics. At the same time, one is constrained by having to harvest all the fruits in a relatively short time in order to avoid any loose fruit picking, over-ripeness, or rotten fruit. Harvesting grains that are considered to be more non-perishable entails relatively fewer challenges of coordination with downstream stages in the agribusiness supply chain.

The cultivators have to establish schedules for sowing, irrigating, and harvesting these activities under resource constraints. The objective is to maximize the yield or profit. The important input variables in model building include market price, market demand, estimated yield, etc. Most of the papers use market price as a very important variable, and thus the effectiveness of the model is indirectly dependent on price forecasting accuracy. Price sensitivity is missing in most of the papers. The majority of the papers provide incremental improvement on or deviation from earlier research with slight new ideas or thoughts. Most of these models are based on either simulated or static/dated data collected weeks/months ago.

Large timber or sugarcane plantations, which have professional management handling the farm decisions, are the most likely users of the available models. Small farmers who may not have professional management can get support for targeted solutions from research institutions that can be facilitated via cooperatives. The large plantations are generally linked to a processing unit such as a sugar mill or a paper mill; thus the demand is a very important but less volatile variable in comparison to the crops being sold in open market scenarios. The models can provide optimal decisions at an aggregate level, but it is difficult to build models at the individual crop level by incorporating variables such as optimal maturity level. This limits the application of robots/machines for these activities.

There is an increase in the application of emerging computer vision technologies coupled with machine learning models to assist farm decisions. Scholars are encouraged to utilize machine learning and deep learning algorithms on images from trees (i.e., image processing) to identify patterns of efficient harvesting for vegetables and provide guidance to farmers for real-time fruit detection within a tree, fruit classification, and guide the operation of fruit harvesting robots. Some of these techniques are discussed in Meshram et al. (2021). Future research can focus on estimating the value of increased ability for farmers to leverage the imaging data on crops and produce that is captured in real-time during automated harvesting of crops, in commanding better prices based on actual grade/quality.

There is also an increase in the availability of soil health and crop images captured by satellite or drones, which can help estimate crop maturity and thus influence irrigation and harvesting decisions. Scholars can utilize big data extracted from new technology in the sugarcane harvesting process to run an analysis for identifying sugarcane harvest periods. This analysis could be based on predictive analytics fed by images of large areas and publicly available optical satellite data (Kavats et al. 2020). Few researchers are addressing strategic questions such as infrastructure investment decisions for building roads, irrigation infrastructure, etc. We next introduce the research on resource management in farming.

4.3. Resource Management

Farm resources management mainly considers management of physical resources (e.g., fertilizers, pesticides, and farm machinery) and workforce management. We describe them below and list the relevant papers for each resource in Table E1 in the E-supplement. The objective is mainly to increase yield or reduce losses in managing these resources. The input parameters in various models include market price and cost of the inputs.

Physical resources: Some of the important issues in managing physical resources are procurement challenges with seeds and fertilizers, such as supplier selection, ensuring quality and quantity, discount and pricing, etc.; issues related to machinery include farm machinery selection, automation, maintenance, capacity utilization, remote operations, tracking, and scheduling. The advancement of technology has made it possible to run several remote operations such as monitoring and tracking, which have opened huge opportunities for farm machinery and equipment management in a more targeted and timely manner (Coble et al. 2016). However, there is limited research in this area from an OM perspective. Farm resources are heavily subsidized by governments across the globe. Fertilizers and pesticides also have a major environmental impact on soil, water, and air and, therefore, are heavily controlled by governments by regulating the supplies as well as by subsidies (Kaygusuz 2010). We discuss this issue in detail in the Government Policy and Interventions sub-section. In the agribusiness research, there is less emphasis on market factors such as demand and more emphasis on usage and maintenance. There is also less emphasis on the optimization of machinery usage or automation of farm activities. The scheduling of equipment use is intertwined with maintenance, as the rate, load, and duration of equipment use influence the need for maintenance. Using real-time data collected through sensors from farm machines and equipment, researchers can investigate the opportunity to optimize machine usage in conjunction with predictive maintenance. For farm input resources, some important questions need to be explored. These include 'when to apply the inputs', 'which inputs to apply', 'how to optimally use the machinery', and 'what the challenges are of technology adoption', etc. Note that the ability to collect real-time data relies on investment in new technology, and one may consider this also as a drawback in small farms.

Workforce: Most of the farm activities are very labor-intensive mostly because the farms are small or inaccessible via machines. The labor requirement is seasonal. For example, huge demand is experienced during sowing and harvesting while there is less demand during the growth period. Most farms depend on seasonal (temporary) labor for farm activities (Klocker et al. 2020). The crop being perishable in nature and having a limited window for optimal sowing and harvesting make it very challenging for the farmers to get the right capacity at the right time. Thus, labor acquisition, labor planning, and labor scheduling are some of the core activities. Lastly, workforce and staffing decisions have to be made for farm activities such as tilling the soil, sowing seeds, spreading fertilizer, sprinkling pesticides, killing weeds, and threshing crops. Workforce requirement depends on environmental conditions, crop rotation, demand, and market prices (Nettle et al. 2010).

The workforce-related literature focuses primarily on manual labor, and there is less emphasis on workforce planning for human-controlled or human-assisted machinery (Pratley 2008). The availability of labor in this sector is often affected by the demand for shared labor in other sectors. Advances in mechanization and skills for labor-assisted mechanization in farming are evolving at an increased pace (Qing et al. 2019). Adopting precision farming and mechanization technologies such as robotics, drones, and autonomous devices will be increasingly crucial to a farm's survival and competitive advantage. Each farm needs to evaluate whether it has the workforce to take full advantage of these technologies or develop a plan to obtain these skills, considering the restrictions on the budget and farm size. There is opportunity to consider the role of platforms in matching demand for labor and equipment with third-party suppliers who can pool their machinery and labor resources for situations wherein there is considerable fragmentation in the presence of numerous small and marginal farmers (Wishon et al. 2015). In conjunction with more granular data captured from the farm, predictive and prescriptive analytics can help researchers find the gap between the current status of labor skills and what to do to close the gap. Based on guidance from analytics, one can hire and schedule the workforce to enhance productivity and yield. Thus, the above-mentioned considerations bring added dimensions for research wherein, in particular small farmers too in the future may have to pool in input resources of farm machinery and labor, and coordinate via cooperatives or outsource some aspects to third-party contractors.

The research in resource management addresses existing problems, including fertilizer allocation, machinery maintenance, and workforce allocations, but places very limited attention on the inclusion of advanced technology such as IoT and drones for farm inputs or machinery maintenance. There is a need to explore existing cases on technology use in farming and address issues related to maintenance, human-machine work coordination, and new machine data. Input prices, finance options, and workforce availability are very much dependent on the political region and thus there is a need to compare and analyze the impacts of government policies on resource management. We next present a brief overview of the farm performance literature.

4.4. Farm Performance

Farm performance topics mainly focus on productivity and risk management. We describe them below and list the relevant papers in Table E1 in the E-supplement.

Productivity: Research on farm productivity has explored several factors that might influence it including policies, social norms, and technology. Productivity in general is measured as a ratio of aggregate output to input. In farm productivity, researchers want to understand the factors (i.e., inputs) that will impact the output (e.g., yield and production).

Risk management: Risk in agribusiness emanates due to uncertainties in weather, the incidence of pests and diseases, yields, government or NGO policies, prices, and other market conditions. Kahan (2008) classifies agribusiness risk into the following five categories: (1) production, due to uncertainty of factors that affect the quantity and quality of farm produce; (2) marketing, driven by the variability and uncertainty of prices; (3) financial, stemming from risks associated with borrowing money to finance the farm business; (4) human, caused by illness and other personal situations impacting labor availability; and (5) institutional, caused by unpredictable changes in governmental policies. Risk management strategies include spare parts management for farm machinery to minimize the risk of delays during breakdowns, working with labor agencies to ensure uninterrupted supply of labor, insurance to cover the financial risk, and forming cooperatives to cover the uncertainty of government policy affecting farming, such as price support and subsidies (i.e., institutional risk).

The farming cycle is limited, and delays in insurance claim payments can often prevent a farmer’s prospects for the next farming cycle. Usually, insurance organizations manage to dispute yield loss data sent by states. Various processes related to the insurance systems or governmental platforms that handle the jobs are manual, leading to backlogs and delays in claim processing and payments (Baskaran and Maher 2021). This problem creates an opportunity for researchers to use artificial intelligence and machine learning to further support the processes related to current crop insurance systems, both avoiding claim delays and lessening the timeline in claim reimbursements. Lin et al. (2020) shed light on how one can use ML and AI to help process claims and make the insurance business efficient in the agriculture business. Further, researchers may use the data on an aggregate level (i.e., farm co-ops) to analyze how a new policy by the local government can help farmers receive the required financial support to develop their farms and keep their operations going. For example, through the Farm Service Agency, the United States Department of Agriculture provides microloans to farmers serving regional food markets for small-scale and diversified operations (USDA 2017). Most of the farm decisions are made based on the information available at a village level. Agricultural productivity depends a lot on the social fabric of the villages as it will determine the workforce availability, input prices, area under production, and crop variety sowed. There is a need to explore how this social fabric of the village can be improved to achieve higher productivity and economic benefits (Serra and Poli, 2015). Productivity also heavily depends on the climate conditions, and thus a change in climate to higher temperatures or frequent extreme weather conditions can have a major impact on productivity. There is a need to investigate the impact of possible climate change scenarios on food production and food security (Zhan et al., 2020). We next focus on emerging themes and opportunities for future research.

5. Emerging Opportunities for Future Research and Conclusion

Overall, we recognize that increased digital connectivity and adoption of emerging technologies will create data-rich environments for facilitating future OM research on farm operations. At the end of each sub-section in Sections 3 and 4, we identify some specific opportunities for future research based on identifying gaps in the literature. In this section, we identify and discuss emergent themes for future research that have not been hitherto addressed as well in the extant literature. We hone in on specific questions, issues, and opportunities for research in the following four domains: Operational Efficiency, Emerging Technologies and IT Platforms, Policy Development and Interventions, and Farmers' Welfare and Support Functions. In particular, it is important to understand how to facilitate the adoption of precision agriculture, IoT, and blockchain to create a data-rich environment with opportunities for targeted intervention for farming. Future research needs to address whether, when, and how small and marginal farmers can also benefit from these technologies.

We summarize specific opportunities for future research in Table 2. In the following subsections, we further elaborate and expand our discussion on these issues.

Table 2: Major Future Research Opportunities

Research Theme	Predictive Analytics Archival and Field-based Empirical Research	Prescriptive Analytics Economic Model-based Research

Operational Efficiency Permeation of Big Data and Emerging Technologies in Improving Operational Efficiency	Assess the impact of crop rotation, crop mix, and land use decisions on soil health, crop yield, and farmer welfare	Develop economic models for crop mix, crop rotation, land use, and harvest scheduling that leverage the estimation of key parameters related to soil and crop characteristics to improve crop yield and resiliency, using granular data generated by emerging technologies (e.g., data from sensors, drones, and satellite images)
Emerging Technologies and IT Platforms Blockchain, Big Data, Drones, IoT, and AI/ML	Use AI/ML techniques to understand the drivers and enablers of farmer participation in agri-platforms and assess their impact on farmer welfare Study the drivers, enablers, and barriers for farmers' adoption of blockchains and precision agriculture, and their ensuing impact on farmer welfare	Develop targeted incentive mechanisms for farmer participation in agri-platforms and adoption of precision agriculture and blockchains based on farmer-type (i.e., marginal, small, and large), soil, crop, and market characteristics, and government subsidies
Policy Development & Interventions Transparency, Accountability, and Sustainability	Assess how transparency via blockchains can influence the accountability for government interventions for sustainability and farmer welfare	Develop government intervention mechanisms for effective adoption of precision agriculture and blockchains Develop mechanisms for guiding public policy to incentivize farmers to make suitable crop rotation and mix decisions to counteract challenges of climate change and any geo-political conflicts
Farmers' Welfare and Support Functions Insurance, Finance, and Human Resources	Predict yield for crops at farm level and evaluate the impact of customized financing schemes, and insurance schemes that ensure timely damage verification using granular data generated by emerging technologies on farmer welfare	Develop customized financing and insurance scheme for farmers that are specific to crop mix, prevalent soil and weather conditions, risk of damage from inclement weather, and yield Develop risk mitigation strategies related to the management of farm labor (e.g., accidents, illness, and death of personnel which can disrupt farm performance)

5.1. Operational Efficiency

An important theme emerges for future research as one is faced with the adoption of precision agriculture or lack thereof in operations of small, medium, and large farms in underdeveloped, developing, and developed countries. How can one estimate key parameters and predict outcomes to economically justify and facilitate the judicious adoption of precision agriculture and increase permeation of technologies for creating data-rich environments equitably to offer targeted guidance for pre-farming decisions and farm operations to influence the metrics of efficiency, effectiveness, resilience, and sustainability, among others? Predictive and prescriptive analytics for facilitating pre-farming and farming decisions will increasingly continue to be of importance because they can influence the quality, quantity, and cost of the farm produce. The emerging technologies provide opportunities to collect farm data at a more granular level and in a timely manner that will help in offering more targeted guidance to farmers. OM researchers can focus on developing dynamic prescriptive models that leverage the improved ability to estimate or predict rainfall, temperature, humidity, soil health, crop growth, fruit maturity, crop quality, pest infestation, crop yield, demand, and market price for crops/produce in a timely manner. Researchers can analyze historical data on sowing patterns, associated weather data, and crop yields to offer guidance to farmers to decide which crop variety and sowing pattern would result in optimal yield. Scholars can assess the impact of crop rotation, crop mix, and land use decisions on soil health, crop yield, and farmer welfare. They can develop economic models for crop mix, crop rotation, land use, and harvest scheduling that leverage the estimation of key parameters related to soil and crop characteristics, using granular data generated by emerging technologies (e.g., data from sensors, drones, and satellite images). For example, they can develop models to offer dynamic guidance for harvesting based on smart sensing of crop maturity.

5.2. Emerging Technologies and IT Platforms

The advent of precision agriculture technology, 5G telecommunication networks, and IT platforms are expected to facilitate interactions between stakeholders in farming in a dynamic manner. The telecom revolution has reached remote locations, providing an Internet connection to rural farmers over mobile devices. The new technological developments impacting farmers and farm operations include but are not limited to blockchain, big data, drones, IoT, and AI/ML. Using blockchain in conjunction with IoT can enhance transparency in agribusiness (see for example Mondal et al. 2019).

OM Researchers can use AI/ML techniques to understand the drivers and enablers of farmer participation in agri-platforms and assess their impact on farmer welfare. Researchers can study the drivers, enablers, and barriers related to farmers’ adoption of blockchains and precision agriculture, as well as their ensuing impact on farmer welfare. OM researchers should develop incentive mechanisms for farmer participation in agri-platforms and adoption of precision agriculture and blockchains based on farmer type (i.e., marginal, small, and large farmers); soil, crop, and market characteristics; and government subsidies.

Researchers can focus on how timely visibility of pricing and other market information, facilitated by increased network connectivity via the use of mobile devices in conjunction with IT platforms, and social media can provide even small and marginal farmers with fair and equitable prices. Scholars can investigate how the increased availability of big data can facilitate cooperation, coordination, group decision making, and bargaining for farmers in a dynamic environment.

5.3. Policy Development and Interventions

Government policies need to facilitate farm productivity to address not only how to feed the growing population but also how to cater to the changing demand. OM researchers need to recognize the changing global trends in demand and supply for both staple and specialty crops. Scholars need to recognize any overdependence on regions that risks the resiliency of their supply (e.g., disruptions on account of geo-political differences and disputes). They need to understand its implications for crop planning, crop rotation, and farm productivity at regional and national levels to ensure food security in an environment that depends on global trade while meeting the needs at national, regional, and local levels. Research on understanding these implications is clearly intertwined with issues such as public policy, land use, irrigation, technology, risk management, and sustainability, among others.

It is important for OM researchers to address many key questions for policy development in a rigorous manner. These questions include but are not limited to: a) what is the impact of government policies on economic, social, and environmental goals for agribusiness? b) how can government policies facilitate the participation of farmers in agribusiness platforms and adoption of emerging technologies (e.g., precision agriculture and blockchains)? c) how can increased transparency from blockchain technology be used to enable sustainability in farm operations? d) what is the impact of increased transparency on the sustenance of small and marginal farmers? and e) to what extent, and how, does big data analytics in conjunction with transparency improve the accountability of government agencies for enhancing productivity in the agriculture sector?

Researchers can leverage the availability of big data to develop guidance for governments to develop agricultural policies in a more targeted manner, based on geographical region, size of farms, and type of crop, among others. The increased focus on sustainability and resilience in agriculture, along with the advent of big data, access to e-marketplaces, transparency, and traceability, provides new opportunities for understanding the implications of government interventions for improving the welfare of farmers. Researchers may use the data on an aggregate level (i.e., farm co-ops) to analyze how a new policy by the local government can help farmers receive the required financial support to develop their farms and keep their operations going.

5.4. Farmers' Welfare and Support Functions

Farmers' welfare is becoming an important concern (Chintapalli and Tang 2021, Tang et al. 2016, Boyabatli et al. 2022). We identify the following important functions that support farmers and add to their welfare, namely, insurance, finance, and human risk management at farms.

Researchers can focus on issues and opportunities related to tailored design and management of farm insurance and finance schemes based on analytics using granular data at the farm level. Based on a recent report by the Global Partnership for Financial Inclusion (GPFI), an inclusive platform for all G20 countries on financial plans and programs, there is a lack of research and use of data on agricultural insurance (GPFI 2015). Usually, insurance organizations manage to dispute yield loss data sent by states. High administrative costs for claims verification lead to more expensive premiums, and insurance requires farmers' certification to reduce false claims, resulting in delayed payouts and low customer satisfaction. Researchers can utilize data collected from drones/unmanned aerial vehicles, which supply high-definition (HD) imagery of soil and crop status and presence of pests (Tran 2018). This helps to expedite the process of evaluating damages and loss. This also can prevent fraud by verifying that the crop was planted on the farm where the farmer has submitted a claim. Researchers can also take weather and soil quality data over time using the planted sensors in the field to enable insurers to underwrite risk and accurately price the insurance product.

Another application of data analytics and AI/ML in agribusiness and insurance is crop-cutting experiments. Crop-cutting experiment is a procedure for determining the crop yield for an area. Crop insurance standards need multiple crop-cutting experiments at every location/farm, leading to millions of experiments across a country to estimate yields. Deep learning (image analytics) can help decrease the requisite number of crop-cutting experiments and facilitate quick claim settlements. Thus, farm research can support agribusiness insurance to provide accurate and timely data required for claims settlement, reduce administrative delays, and minimize false claims. Research is needed for analyzing crop data during adverse periods of drought, floods, fire, or pest infestation, in near real time, to help the insurance companies provide fair and timely compensation to the farmers.

In regard to farm finance, lenders see an increased risk of lending to a new farmer, and they are also less familiar with small, diversified farming operations. Hence, they prefer to collect data at the farm level to learn more about the associated risks, prior to lending (Song 2021). Financial institutions and lenders are also not as comfortable with uncertain and seasonal cash flows, which vary from crop to crop and cycle to cycle, depending on the weather and other agricultural risks. These fluctuations and uncertainty can be discouraging for traditional lenders and financial organizations, in turn limiting funding for marginal farmers or subjecting them to considerably higher lending rates. To deal with this uncertainty, lenders prefer to restrict their lending portfolio to fewer crops, collect data, and understand better these crop cycles and the factors that influence them. Going forward, lenders can leverage big data and analytics to identify and approach these risks better for a wider variety of crops and also for small and diversified farms.

Researchers can help lenders identify and evaluate the risk factors and prescribe how farmers can effectively mitigate seasonal risks to increase productivity and market value. It can also enable lenders to better understand the risks and benefits associated with crop planning, crop rotation, and land use and facilitate farmers' decision-making to mitigate the risk associated with crop cycles.

Lastly, there is also a paucity of research in the OM journals on institutional and human risk management in farming. Researchers need to investigate risk mitigation strategies related to the management of labor and human resources (e.g., accidents, illness, and death of personnel, which can disrupt farm performance) and institutional risk (e.g., food quality regulations for exporting crops and the level of price or income support payments).

In the end, we want to re-emphasize that agribusiness research undertaken by OM researchers should support Sustainable Development Goal 2 of the Food and Agriculture Organization of the United Nations. The excerpt of this goal also stated at the outset in the introduction is: "End hunger, achieve food security and improved nutrition and promote sustainable agriculture……. These worrying trends coincide with the diminishing availability of land; increasing soil and biodiversity degradation; and more frequent and severe weather events. The impact of climate change on agriculture compounds the situation.” Given the daunting challenge, the agribusiness sector will also benefit greatly from a multidisciplinary research approach that includes OM researchers, agricultural scientists, experts in finance and insurance, and information technology. Gaining access to requisite data will also require collaboration between universities, governments, NGOs, farmers, and IT platform providers, among others. The focus of this paper is on the upstream operations of the agribusiness supply chain. We suggest that similar review papers should be undertaken on the downstream end of the agribusiness supply chain.

Endnotes

1. There are 298 papers that have been included in our paper. Of these, we list 88 papers in the main manuscript and 210 papers in the E-supplement. The 298 papers include 256 papers that we have analyzed, 17 previous survey papers, and 25 papers we have used for clarifications and future research agendas. The research on stakeholder engagement for farming in a digital era is emerging as more data is available. Thus, to help POM readers explore more research opportunities in this area, the authors mainly focused on 88 papers related to stakeholder engagement for farming in a digital era in the main manuscript. Hence, the discussion on operational efficiency in farming is shortened and mainly relegated to the appendix.
2. In India, a farmer with a bare subsistence level of income who may also work as an agricultural laborer for cultivation of one’s own land that is no larger than 2.5 acres is termed a marginal farmer, see https://www.rbi.org.in/scripts/BS_CircularIndexDisplay.aspx?Id=4190#:~:text='Marginal%20Farmer'%20means%20a%20farmer,2%20hectares%20(5%20acres).

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E-Supplement

Table E1: Categories of Papers for Operational Efficiency in Farming

Note: Citation for each paper listed in Table E1 is given at the end of this E-Supplement

Reference to Article	Source title	Sub-Category	Type of Data	Analysis Techniques
An et al. (2015)	Production and Operations Management	Contracting and Cooperative Farming	No Data	Game Theory
Ayvaz-Çavdaroğlu et al. (2021)	Production and Operations Management	Contracting and Cooperative Farming	Real	Mathematical Programming
Burer et al. (2009)	European Journal of Operational Research	Contracting and Cooperative Farming	No Data	Game Theory
Chen and Chen (2021)	Production and Operations Management	Contracting and Cooperative Farming	No Data	Game Theory
Federgruen et al. (2019)	Manufacturing and Service Operations Management	Contracting and Cooperative Farming	No data	Mathematical Programming
Hu et al. (2019)	Management Science	Contracting and Cooperative Farming	No data	Game Theory
Niu et al. (2016)	European Journal of Operational Research	Contracting and Cooperative Farming	No data	Game Theory
Palsule-Desai (2015)	Transportation Research Part E	Contracting and Cooperative Farming	No data	Game Theory
Puchalsky et al. (2018)	International Journal of Production Economics	Contracting and Cooperative Farming	Archival	AI & Machine Learning
Qian (2021)	European Journal of Operational Research	Contracting and Cooperative Farming	Hypothetical	Mathematical Programming
Rajput and Venkataraman (2021)	Annals of Operations Research	Contracting and Cooperative Farming	No Data	Game Theory
Ryan (1999)	European Journal of Operational Research	Contracting and Cooperative Farming	No data	Game Theory
Shi et al. (2019)	Production and Operations Management	Contracting and Cooperative Farming	No data	Mathematical Programming
Tang et al. (2016)	European Journal of Operational Research	Contracting and Cooperative Farming	No data	Game Theory
Assa et al. (2021)	European Journal of Operational Research	Farm Finance and Insurance	No Data	Game Theory
Colin (2009)	European Journal of Operational Research	Farm Finance and Insurance	Real	Mathematical Programming
da Silva et al. (2020)	Annals of Operations Research	Farm Finance and Insurance	Archival	Statistical Analysis
Heikkinen and Pietola (2009)	European Journal of Operational Research	Farm Finance and Insurance	Real	Mathematical Programming
Martins and Lucato (2018)	International Journal of Operations and Production Management	Farm Finance and Insurance	Survey	Statistical Analysis
Qian and Olsen (2020)	Manufacturing and Service Operations Management	Farm Finance and Insurance	No data	Decision Analysis
Viaggi et al. (2010)	European Journal of Operational Research	Farm Finance and Insurance	Real	Mathematical Programming
Yi et al. (2021)	Production and Operations Management	Farm Finance and Insurance	No data	Mathematical Programming
Zhou et al. (2020)	International Journal of Production Research	Farm Finance and Insurance	No data	Decision Analysis
Ahumada and Villalobos (2011)	International Journal of Production Economics	Farm Operations - Harvesting	No data	Mathematical Programming

AitSahlia et al. (2011)	Annals of Operations Research	Farm Operations - Harvesting	Real	Mathematical Programming
Albornoz et al. (2021)	Annals of Operations Research	Farm Operations - Harvesting	Real	Mathematical Programming
Aliano et al. (2021)	Computers and Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Aliano Filho et al. (2019)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Meta-Heuristics
Alonso-Ayuso et al. (2011)	Annals of Operations Research	Farm Operations - Harvesting	No data	Mathematical Programming
Alonso-Ayuso et al. (2020)	Computers and Operations Research	Farm Operations - Harvesting	Real	Mathematical Programming
Álvarez-Miranda et al. (2018)	European Journal of Operational Research	Farm Operations - Harvesting	Real	Mathematical Programming
Bhattacharya (2006)	Journal of the Operational Research Society	Farm Operations - Harvesting	Real	Statistical Analysis
Bohle et al. (2010)	European Journal of Operational Research	Farm Operations - Harvesting	Real	Mathematical Programming
Bont et al. (2015)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Borges et al. (2014)	European Journal of Operational Research	Farm Operations - Harvesting	Hypothetical	Meta-Heuristics
Borodin et al. (2014)	International Journal of Production Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Borodin et al. (2015)	European Journal of Operational Research	Farm Operations - Harvesting	No data	Mathematical Programming
Caixeta-Filho (2006)	Journal of the Operational Research Society	Farm Operations - Harvesting	Real	Mathematical Programming
Caro et al. (2003)	Production and Operations Management	Farm Operations - Harvesting	Real	Mathematical Programming
Carvajal et al. (2013)	Operations Research	Farm Operations - Harvesting	Real	Mathematical Programming
Castellano et al. (2020)	Annals of Operations Research	Farm Operations - Harvesting	Archival	Statistical Analysis
Chauhan et al. (2011)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Heuristics
Clark et al. (2000)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Cominetti and Piazza (2009)	Mathematics of Operations Research	Farm Operations - Harvesting	No data	Mathematical Programming
Constantino and Martins (2018)	European Journal of Operational Research	Farm Operations - Harvesting	Real	Mathematical Programming
Constantino et al. (2008)	Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Darby-Dowman et al. (2000)	Journal of the Operational Research Society	Farm Operations - Harvesting	Real	Mathematical Programming
Dems et al. (2015)	Annals of Operations Research	Farm Operations - Harvesting	Real	Mathematical Programming
Dems et al. (2017)	European Journal of Operational Research	Farm Operations - Harvesting	Real	Mathematical Programming
Devadoss and Luckstead (2010)	International Journal of Production Economics	Farm Operations - Harvesting	Real	Statistical Analysis
Duvemo et al. (2014)	Annals of Operations Research	Farm Operations - Harvesting	Archival	Simulation
Epstein et al. (1999)	European Journal of Operational Research	Farm Operations - Harvesting	Real	Mathematical Programming
Escallón-Barrios et al. (2020)	Annals of Operations Research	Farm Operations - Harvesting	Real	Heuristics
Ferrer et al. (2008)	International Journal of Production Economics	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Florentino et al. (2018)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Meta-Heuristics
Florentino et al. (2020)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Golenko-Ginzburg et al. (1996)	International Journal of Production Economics	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Gómez et al. (2011)	Annals of Operations Research	Farm Operations - Harvesting	Real	Heuristics
Gómez-Lagos et al. (2020)	European Journal of Operational Research	Farm Operations - Harvesting	Real	Meta-Heuristics

Haouari and Azaiez (2001)	European Journal of Operational Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Hellman (1977)	European Journal of Operational Research	Farm Operations - Harvesting	No data	Mathematical Programming
Higgins and Laredo (2006)	Journal of the Operational Research Society	Farm Operations - Harvesting	Real	Mathematical Programming
Jana et al. (2016)	International Journal of Production Economics	Farm Operations - Harvesting	Hypothetical	Meta-Heuristics
Jena and Poggi (2013)	European Journal of Operational Research	Farm Operations - Harvesting	Real	Mathematical Programming
Jones and Ohlmann (2008)	European Journal of Operational Research	Farm Operations - Harvesting	No data	Mathematical Programming
Jonkman et al. (2019)	European Journal of Operational Research	Farm Operations - Harvesting	Real	Mathematical Programming
Junqueira and Morabito (2019)	International Journal of Production Economics	Farm Operations - Harvesting	Real	Mathematical Programming
Könny and Tóth (2013)	European Journal of Operational Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Lamsal et al. (2016)	International Journal of Production Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Lamsal et al. (2017)	Transportation Science	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
LIANG et al. (1971)	Operations Research	Farm Operations - Harvesting	Real	Mathematical Programming
Liski and Nummi (1996)	International Journal of Production Economics	Farm Operations - Harvesting	Hypothetical	Statistical Analysis
Liu (2001)	Computers and Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Mann et al. (2016)	International Journal of Production Research	Farm Operations - Harvesting	Hypothetical	Simulation
Neto et al. (2017)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Neto et al. (2020)	European Journal of Operational Research	Farm Operations - Harvesting	Hypothetical	Heuristics
Nureize et al. (2014)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Statistical Analysis
Ortuño and Vitoriano (2011)	Annals of Operations Research	Farm Operations - Harvesting	Real	Mathematical Programming
Pagnoncelli and Piazza (2017)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Petrasek et al. (2015)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Piazza and Pagnoncelli (2014)	Annals of Operations Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Recio et al. (2003)	Decision Support Systems	Farm Operations - Harvesting	Real	Decision Analysis
Reeves and Haight (2000)	Annals of Operations Research	Farm Operations - Harvesting	Archival	Statistical Analysis
Sanei Bajgiran et al. (2017)	International Journal of Production Research	Farm Operations - Harvesting	Hypothetical	Mathematical Programming
Sanjika and Bezuidenhout (2016)	International Journal of Production Research	Farm Operations - Harvesting	Survey	Statistical Analysis
Semenzato et al. (1995)	Journal of the Operational Research Society	Farm Operations - Harvesting	Hypothetical	Simulation
Sethanan and Neungmatcha (2016)	European Journal of Operational Research	Farm Operations - Irrigation	Hypothetical	Meta-Heuristics
SORENSEN and GILHEANY (1970)	Management Science	Farm Operations - Irrigation	Real	Simulation
St. John and Tóth (2015)	Annals of Operations Research	Farm Operations - Irrigation	Hypothetical	Heuristics
Van Elderen (1980)	European Journal of Operational Research	Farm Operations - Irrigation	Hypothetical	Mathematical Programming
Veliz et al. (2015)	Annals of Operations Research	Farm Operations - Irrigation	Hypothetical	Heuristics
Wei and Murray (2015)	Annals of Operations Research	Farm Operations - Irrigation	Hypothetical	Heuristics
Widodo et al. (2006)	European Journal of Operational Research	Farm Operations - Irrigation	No data	Mathematical Programming

Wijngaard (1988)	European Journal of Operational Research	Farm Operations - Irrigation	Hypothetical	Heuristics
Yu and Leung (2009)	International Journal of Production Economics	Farm Operations - Irrigation	No data	Mathematical Programming
Zhang and Swaminathan (2020)	Manufacturing and Service Operations Management	Farm Operations - Irrigation	Archival	Mathematical Programming
Zhang et al. (2011)	Annals of Operations Research	Farm Operations - Irrigation	Hypothetical	Mathematical Programming
Allen and Schuster (2004)	Manufacturing and Service Operations Management	Farm Operations - Irrigation	Real	Mathematical Programming
Baležentis et al. (2020)	Decision Sciences	Farm Operations - Irrigation	Archival	Statistical Analysis
Balk et al. (2020)	Computers and Operations Research	Farm Operations - Irrigation	Archival	Mathematical Programming
Bokusheva et al. (2012)	International Journal of Production Economics	Farm Operations - Irrigation	Archival	Statistical Analysis
Cong et al. (2017)	Annals of Operations Research	Farm Operations - Irrigation	No data	Mathematical Programming
De Buck et al. (1999)	European Journal of Operational Research	Farm Operations - Irrigation	Real	Mathematical Programming
DeVuyst et al. (2009)	Transportation Research Part E	Farm Operations - Irrigation	Real	Statistical Analysis
Dimara et al. (2005)	European Journal of Operational Research	Farm Operations - Irrigation	Real	mathematical Programming
Ge et al. (2019)	International Journal of Production Research	Farm Operations - Irrigation	Hypothetical	Simulation
Georganta (1997)	International Journal of Production Economics	Farm Operations - Irrigation	Hypothetical	Statistical Analysis
Gómez-Limón et al. (2003)	European Journal of Operational Research	Farm Operations - Irrigation	Real	Decision Analysis
Kerstens et al. (2018)	International Journal of Production Economics	Farm Operations - Irrigation	Archival	Statistical Analysis
Lien et al. (2007)	European Journal of Operational Research	Farm Operations - Planting	No data	Mathematical Programming
Lien et al. (2011)	Annals of Operations Research	Farm Operations - Planting	No data	Simulation
Lien et al. (2018)	International Journal of Production Economics	Farm Operations - Planting	Archival	Mathematical Programming
Mosquera et al. (2011)	Annals of Operations Research	Farm Operations - Planting	Real	Decision Analysis
Nagendra et al. (2020)	Annals of Operations Research	Farm Operations - Planting	Big Data	Decision Analysis
Odeck (2009)	Omega	Farm Operations - Planting	Archival	Mathematical Programming
Prasad et al. (1992)	International Journal of Production Economics	Farm Operations - Planting	Real	Mathematical Programming
Prasad et al. (1994)	International Journal of Production Economics	Farm Operations - Planting	Real	Mathematical Programming
Romero (2000)	Annals of Operations Research	Farm Operations - Planting	Hypothetical	Decision Analysis
Santini et al. (2021)	European Journal of Operational Research	Farm Operations - Planting	Real	Mathematical Programming
Serra and Oude Lansink (2014)	European Journal of Operational Research	Farm Performance - Productivity	Archival	Statistical Analysis
Serra and Poli (2015)	European Journal of Operational Research	Farm Performance - Productivity	Archival	Mathematical Programming
Singbo et al. (2015)	European Journal of Operational Research	Farm Performance - Productivity	Archival	Mathematical Programming
Zhan et al. (2020)	Annals of Operations Research	Farm Performance - Productivity	Archival	Mathematical Programming
Akkaya et al. (2021)	Manufacturing and Service Operations Management	Farm Performance - Productivity	Real	Game Theory
Alizamir et al. (2019)	Management Science	Farm Performance - Productivity	Real	Game Theory
Amores and Contreras (2009)	European Journal of Operational Research	Farm Performance - Productivity	Archival	Mathematical Programming

Ayouba et al. (2019)	European Journal of Operational Research	Farm Performance - Productivity	Archival	Statistical Analysis
Baum et al. (1984)	Computers and Operations Research	Farm Performance - Productivity	Real	Mathematical Programming
Cabrini et al. (2004)	Manufacturing and Service Operations Management	Farm Performance - Productivity	No data	Mathematical Programming
Chen and Tang (2015)	Production and Operations Management	Farm Performance - Productivity	No data	Game Theory
Cherchye and Van Puyenbroeck (2007)	Omega	Farm Performance - Risk Management	Real	Statistical Analysis
Chintapalli and Tang (2021a)	Management Science	Farm Performance - Risk Management	No data	Game Theory
Chintapalli and Tang (2021b)	Production and Operations Management	Farm Performance - Risk Management	No data	Mathematical Programming
García-Alonso et al. (2010)	European Journal of Operational Research	Farm Performance - Risk Management	Real	Statistical Analysis
Guda et al. (2021)	Production and Operations Management	Farm Performance - Risk Management	No data	Game Theory
Gupta et al. (2017)	Production and Operations Management	Farm Performance - Risk Management	Real	Mathematical Programming
He et al. (2018)	Production and Operations Management	Farm Performance - Risk Management	No data	Game Theory
Jiang et al. (2021)	International Journal of Production Research	Farm Performance - Risk Management	No data	Game Theory
Liao and Chen (2017)	Production and Operations Management	Farm Performance - Risk Management	No data	Game Theory
Liao et al. (2019)	Manufacturing and Service Operations Management	Farm Performance - Risk Management	No data	Game Theory
Minviel and De Witte (2017)	European Journal of Operational Research	Farm Performance - Risk Management	Archival	Statistical Analysis
Önal (1988)	European Journal of Operational Research	Farm Performance - Risk Management	Real	Mathematical Programming
Önal et al. (1995)	Computers and Operations Research	Farm Performance - Risk Management	Real	Mathematical Programming
Owsiński and Romanowicz (1985)	European Journal of Operational Research	Farm Performance - Risk Management	Real	Mathematical Programming
Serra et al. (2014)	European Journal of Operational Research	Farm Performance - Risk Management	Archival	Mathematical Programming
Sueyoshi (1999)	Omega	Government Policy and Interventions	Real	Statistical Analysis
Sueyoshi et al. (1998)	Omega	Government Policy and Interventions	Real	Mathematical Programming
Sumpsi et al. (1997)	European Journal of Operational Research	Government Policy and Interventions	Real	Decision Analysis
Tang et al. (2015)	Production and Operations Management	Government Policy and Interventions	No data	Game Theory
Teich et al. (1995)	European Journal of Operational Research	Government Policy and Interventions	Real	Decision Analysis
Wade James and Heady Earl (1978)	Management Science	Government Policy and Interventions	Real	Mathematical Programming
Ye et al. (2021)	Naval Research Logistics	Government Policy and Interventions	No data	Game Theory
Albornoz et al. (2020)	Annals of Operations Research	Government Policy and Interventions	Hypothetical	Mathematical Programming
Alfandari et al. (2011)	Annals of Operations Research	Government Policy and Interventions	No data	Mathematical Programming
Alfandari et al. (2015)	European Journal of Operational Research	Government Policy and Interventions	Hypothetical	Mathematical Programming
Arondel and Girardin (2000)	European Journal of Operational Research	Government Policy and Interventions	Real	Decision Analysis
Boyabatli et al. (2019)	Management Science	Government Policy and Interventions	No data	Mathematical Programming
Brulard et al. (2019)	International Journal of Production Research	Government Policy and Interventions	Real	Mathematical Programming
Calija et al. (2001)	Annals of Operations Research	Government Policy and Interventions	Real	Simulation

Cervantes-Gaxiola et al. (2020)	European Journal of Operational Research	Government Policy and Interventions	Archival	Mathematical Programming
Clarke (1989)	European Journal of Operational Research	Government Policy and Interventions	Real	Mathematical Programming
Costa et al. (2014)	Annals of Operations Research	Government Policy and Interventions	Real	Mathematical Programming
De Oliveira Florentino and Pato (2014)	Journal of the Operational Research Society	Government Policy and Interventions	Hypothetical	Meta-Heuristics
dos Santos et al. (2011)	Annals of Operations Research	Government Policy and Interventions	Real	Mathematical Programming
Eto (1991)	Omega	Government Policy and Interventions	Real	Mathematical Programming
Filippi et al. (2017)	Computers and Operations Research	Government Policy and Interventions	Real	Mathematical Programming
Haneveld and Stegeman (2005)	European Journal of Operational Research	Government Policy and Interventions	No data	Mathematical Programming
Huh and Lall (2013)	Production and Operations Management	Government Policy and Interventions	Real	Mathematical Programming
Jones et al. (2001)	Manufacturing and Service Operations Management	Government Policy and Interventions	Real	Mathematical Programming
Kazakçi et al. (2007)	Journal of the Operational Research Society	Government Policy and Interventions	Real	Mathematical Programming
Makowski et al. (2001)	European Journal of Operational Research	Government Policy and Interventions	Real	Mathematical Programming
Pakawanich et al. (2021)	Journal of the Operational Research Society	Government Policy and Interventions	Hypothetical	Heuristics
Rădulescu et al. (2014)	Annals of Operations Research	Government Policy and Interventions	Hypothetical	Heuristics
Regis Mauri (2019)	European Journal of Operational Research	Government Policy and Interventions	Hypothetical	Mathematical Programming
Ridier et al. (2016)	European Journal of Operational Research	Pre-farming Decisions - Crop Mix	Hypothetical	Simulation
Saedt et al. (1991)	European Journal of Operational Research	Pre-farming Decisions - Crop Mix	Real	Decision Analysis
Santos et al. (2015)	European Journal of Operational Research	Pre-farming Decisions - Crop Mix	Real	Mathematical Programming
Siskos et al. (1994)	European Journal of Operational Research	Pre-farming Decisions - Crop Mix	Real	Mathematical Programming
Tan and Fong (1988)	European Journal of Operational Research	Pre-farming Decisions - Crop Mix	Real	Mathematical Programming
Whan et al. (1978)	Journal of the Operational Research Society	Pre-farming Decisions - Crop Mix	Hypothetical	Mathematical Programming
Yoshimoto and Shoji (1998)	European Journal of Operational Research	Pre-farming Decisions - Crop Mix	Real	Mathematical Programming
Žnidaršič et al. (2008)	European Journal of Operational Research	Pre-farming Decisions - Crop Mix	No data	Decision Analysis
Agrell et al. (2004)	European Journal of Operational Research	Pre-farming Decisions - Crop Mix	Real	Decision Analysis
Ahumada and Villalobos (2011)	Annals of Operations Research	Pre-farming Decisions - Crop Mix	Real	Mathematical Programming
Almiñana et al. (2008)	IIE Transactions (Institute of Industrial Engineers)	Pre-farming Decisions - Crop Mix	Real	Mathematical Programming
Almiñana et al. (2010)	Omega	Pre-farming Decisions - Crop Mix	Real	Decision Analysis
Annetts and Audsley (2002)	Journal of the Operational Research Society	Pre-farming Decisions - Crop Mix	Real	Mathematical Programming
Ata et al. (2019)	Operations Research	Pre-farming Decisions - Crop Mix	Real	Mathematical Programming
Azaiez (2002)	European Journal of Operational Research	Pre-farming Decisions - Crop Mix	Hypothetical	Decision Analysis
Azaiez and Hariga (2001)	European Journal of Operational Research	Pre-farming Decisions - Crop Rotation	Hypothetical	Mathematical Programming
Barreteau and Bousquet (2000)	Annals of Operations Research	Pre-farming Decisions - Crop Rotation	Real	Mathematical Programming
Benhamou et al. (2020)	International Journal of Production Economics	Pre-farming Decisions - Crop Rotation	No data	Mathematical Programming

Biswas and Pal (2005)	Omega	Pre-farming Decisions - Crop Rotation	Real	Mathematical Programming
Bloemhof-Ruwaard and Hendrix (1996)	European Journal of Operational Research	Pre-farming Decisions - Crop Rotation	Hypothetical	Mathematical Programming
Bochtis et al. (2012)	Decision Support Systems	Pre-farming Decisions - Crop Rotation	Hypothetical	Mathematical Programming
Bravo and Gonzalez (2009)	European Journal of Operational Research	Pre-farming Decisions - Crop Rotation	Archival	Mathematical Programming
Crespo et al. (2011)	Annals of Operations Research	Pre-farming Decisions - Crop Rotation	No data	Decision Analysis
Dawande et al. (2013)	Manufacturing and Service Operations Management	Pre-farming Decisions - Crop Rotation	No data	Mathematical Programming
Deng and Gibson (2020)	Annals of Operations Research	Pre-farming Decisions - Crop Rotation	Archival	Statistical Analysis
Deris and Ohta (1990)	Journal of the Operational Research Society	Pre-farming Decisions - Crop Rotation	Real	Mathematical Programming
Eben-Chaime et al. (2011)	International Journal of Production Economics	Pre-farming Decisions - Crop Rotation	Hypothetical	Simulation
Elimam (1995)	European Journal of Operational Research	Pre-farming Decisions - Crop Rotation	Real	Decision Analysis
Fotio Tiotsop et al. (2020)	Computers and Operations Research	Pre-farming Decisions - Crop Rotation	Hypothetical	Mathematical Programming
García-Alonso et al. (2014)	Annals of Operations Research	Pre-farming Decisions - Crop Rotation	Real	Meta-Heuristics
Gebrezgabher et al. (2014)	European Journal of Operational Research	Pre-farming Decisions - Land-use	Hypothetical	Heuristics
Ghosh et al. (2005)	International Journal of Production Economics	Pre-farming Decisions - Land-use	Real	Game Theory
Glen (1988)	European Journal of Operational Research	Pre-farming Decisions - Land-use	Real	Mathematical Programming
Gómez-Limón and Martínez (2006)	European Journal of Operational Research	Pre-farming Decisions - Land-use	Real	Decision Analysis
Gonçalves et al. (2014)	Annals of Operations Research	Pre-farming Decisions - Land-use	Real	Heuristics
Han et al. (2020)	European Journal of Operational Research	Pre-farming Decisions - Land-use	Hypothetical	Decision Analysis
Huang (1998)	European Journal of Operational Research	Pre-farming Decisions - Land-use	Real	Mathematical Programming
Ines Minguez et al. (1988)	Journal of the Operational Research Society	Pre-farming Decisions - Land-use	Real	Mathematical Programming
Krcmar et al. (2001)	European Journal of Operational Research	Resource Management - Physical Resources	Real	Mathematical Programming
Levy and Caputo (2008)	European Journal of Operational Research	Resource Management - Physical Resources	No data	Mathematical Programming
López-Baldovin et al. (2006)	Journal of the Operational Research Society	Resource Management - Physical Resources	Real	Decision Analysis
Maatman et al. (2002)	Operations Research	Resource Management - Physical Resources	Real	Mathematical Programming
Marques Gonçalves & Vaz Pato (2000)	Annals of Operations Research	Resource Management - Physical Resources	Real	Mathematical Programming
Martens et al. (2012)	Decision Sciences	Resource Management - Physical Resources	Hypothetical	Mathematical Programming
Martins and Marques (2007)	European Journal of Operational Research	Resource Management - Physical Resources	Real	Mathematical Programming
Maschler et al. (2019)	Annals of Operations Research	Resource Management - Physical Resources	Archival	Decision Analysis
Piot-Lepetit (2014)	Annals of Operations Research	Resource Management - Physical Resources	Hypothetical	Mathematical Programming
Raju and Pillai (1999)	European Journal of Operational Research	Resource Management - Physical Resources	Real	Decision Analysis
Raju et al. (2006)	Computers and Operations Research	Resource Management - Physical Resources	Real	Mathematical Programming
Robert et al. (2018)	European Journal of Operational Research	Resource Management - Physical Resources	Real	Mathematical Programming
Sapountzis (1991)	European Journal of Operational Research	Resource Management - Physical Resources	Archival	Statistical Analysis

Schreider et al. (2013)	Annals of Operations Research	Resource Management - Physical Resources	No data	Game Theory
Sharma (1991)	European Journal of Operational Research	Resource Management - Physical Resources	Hypothetical	Mathematical Programming
Sharma and Jana (2009)	International Journal of Production Economics	Resource Management - Physical Resources	Real	Decision Analysis
Shoemaker Christine (1982)	Operations Research	Resource Management - Physical Resources	Hypothetical	Mathematical Programming
Skevas et al. (2012)	European Journal of Operational Research	Resource Management - Physical Resources	Archival	Mathematical Programming
Skevas et al. (2014)	European Journal of Operational Research	Resource Management - Physical Resources	Archival	Mathematical Programming
Stoecker et al. (1985)	Management Science	Resource Management - Physical Resources	Real	Mathematical Programming
Sun et al. (2000)	Annals of Operations Research	Resource Management - Physical Resources	Real	Statistical Analysis
Thiel (2009)	Journal of the Operational Research Society	Resource Management - Physical Resources	Real	Mathematical Programming
Upcraft et al. (1989)	Journal of the Operational Research Society	Resource Management - Physical Resources	Real	Mathematical Programming
Vitoriano et al. (2003)	European Journal of Operational Research	Resource Management - Physical Resources	Real	Mathematical Programming
Vizvári and Lakner (2014)	Annals of Operations Research	Resource Management - Workforce	Real	Mathematical Programming
Vizvári et al. (2011)	Annals of Operations Research	Resource Management - Workforce	No data	Mathematical Programming
Wang et al. (2020)	International Journal of Production Research	Resource Management - Workforce	Hypothetical	Mathematical Programming
Wishon et al. (2015)	International Journal of Production Economics	Resource Management - Workforce	Real	Mathematical Programming
dos Santos et al. (2010)	European Journal of Operational Research	Sustainability	Real	Mathematical Programming
Elfkih et al. (2009)	Journal of the Operational Research Society	Sustainability	Real	Mathematical Programming
Gomes et al. (2009)	Annals of Operations Research	Sustainability	Archival	Statistical Analysis
Hosseini-Motlagh et al. (2020)	International Journal of Production Research	Sustainability	No data	Game Theory
Picazo-Tadeo et al. (2012)	European Journal of Operational Research	Sustainability	Archival	Mathematical Programming
Ranga Prabodanie et al. (2014)	Annals of Operations Research	Sustainability	Hypothetical	Mathematical Programming
Wang et al. (2020)	International Journal of Production Economics	Sustainability	Hypothetical	Mathematical Programming
Aubert et al. (2012)	Decision Support Systems	Technology and Platforms	Survey	Statistical Analysis
Chen et al. (2013)	Production and Operations Management	Technology and Platforms	No data	Game Theory
Chen et al. (2015)	Production and Operations Management	Technology and Platforms	No data	Game Theory
Kurkalova and Carter (2017)	Decision Support Systems	Technology and Platforms	No data	Simulation
Lowe and Preckel (2004)	Manufacturing and Service Operations Management	Technology and Platforms	No data	Decision Analysis
Parker et al. (2016)	Management Science	Technology and Platforms	Archival	Statistical Analysis
Petridis et al. (2020)	Annals of Operations Research	Technology and Platforms	Archival	Statistical Analysis
Zhang and Goddard (2007)	Decision Support Systems	Technology and Platforms	Hypothetical	Decision Analysis
Zhou et al. (2021)	Manufacturing and Service Operations Management	Technology and Platforms	No data	Game Theory

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