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Machine learning-based farm risk management: A systematic mapping review

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ABSTRACT

Farms face various risks such as uncertainties in the natural growth process, obtaining adequate financing, volatile input and output prices, unpredictable changes in farm-related policy and regulations, and farmers‘ personal health problems. Accordingly, farmers have to make decisions to be prepared for such situations under risk or mitigate their impacts to maintain essential functions. Increasingly, a data-driven perspective is warranted where machine learning (ML) has become an essential tool for automatic extraction of useful information to support decision-making in farm management as well as risk management. ML's role in farm risk management (FRM) has recently increased with advances in technology and digitalization. This paper provides a literature review in the form of a systematic mapping study to identify the publications, trends, active research communities, and detailed reviews on the use of ML methods for FRM. Accordingly, nine research/mapping questions are designed to extract the required information. In total, we retrieved 1819 papers, of which 746 papers were selected based on the defined exclusion criteria for a detailed review. We categorized the studies based on the addressed risk types (e.g., production risk), assessments that addressed risk components (e.g., resilience), used ML types (e.g., supervised learning) and algorithms ranging from regression modeling to deep learning, addressed ML tasks (e.g., classification), data types (e.g., images), and farm types (e.g., crop-based farm). The results reveal that there is a significant increase in employing ML methods including deep learning and convolutional neural networks for FRM in recent years. The production risk and impact/damage assessment are the most frequently addressed risk type and assessment that addressed risk components in ML-FRM, respectively. In addition, research gaps and open problems are identified and accordingly insights and recommendations from risk management and machine learning perspectives are provided for future studies including the need for ML methods for different risk types (e.g., financial risk), assessments addressing different risk components (e.g., resilience assessment), and developing more advanced ML methods (e.g., reinforcement learning) for FRM.

1. Introduction

One of the most important management tasks of a farmer is to deal with the plethora of risks that may occur on a farm. Evaluating and quantifying risk can provide crucial information to support decision-making on the farm at any time. Risk can be assessed based on its components, i.e., response, recovery, mitigation, and preparedness, (Coppola, 2015; UNISDR, 2009) using different evaluations including vulnerability, resilience, and impact (Ghaffarian et al., 2018; Meuwissen et al., 2019). Depending on the stage and aim, each of these aspects can be assessed to provide information for farm risk management (FRM). For example, in case of an agricultural pest or disease outbreak, the farmer needs to have an impact assessment to extract its effects on production or detect the damaged crops/animals to response and act quickly and reduce further impacts. In other examples, assessing the resilience of the farm to climate change (Luo et al., 2017; Nyasimi et al., 2017) or drought (Sennhenn et al., 2017) is important for a farmer to make decisions and be prepared to cope with such situations. Therefore, assessing farm-level risk in general or any of its components is important to understand the situation and make decisions accordingly. Recent advances in technology including computer facilities and sensors provide big data as well as automatic computer-based processing methods

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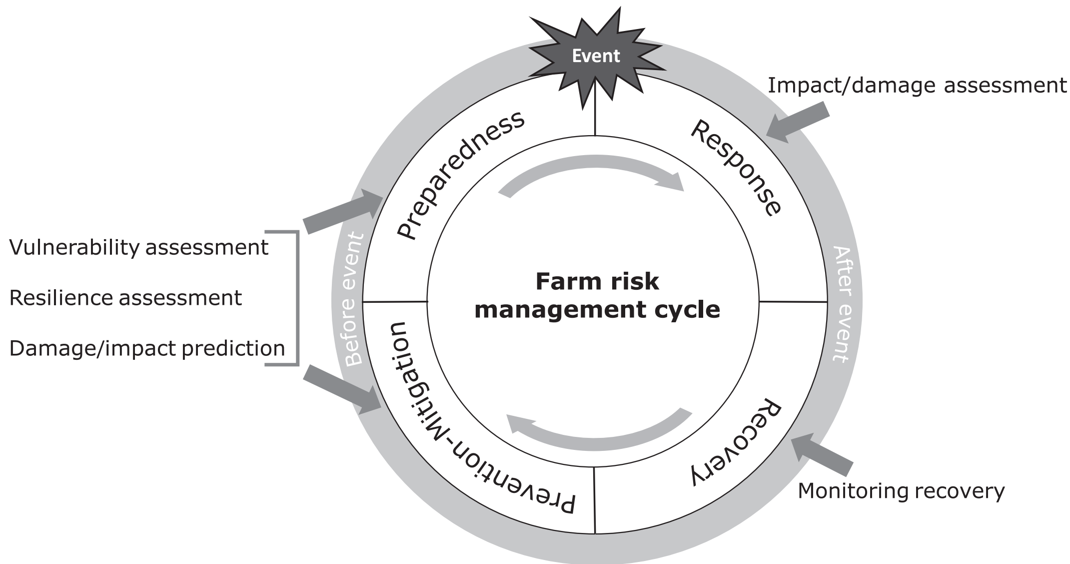

Fig. 1. Components of the farm risk management cycle and associated assessments in which machine learning methods can be used.

to evaluate the risks at any time (Woodard, 2016). In recent years, machine learning (ML) has gained attention in different science fields including (agricultural) economics (Athey, 2018). It is increasingly being used for farm risk analyses and other fields such as disaster risk management (Ghaffarian et al., 2019; Ghaffarian et al., 2020; Kerle et al., 2019). ML methods provide accurate data processing results in an automated manner to assess the risk in general (Almeria et al., 2009; Chavez et al., 2015; Esgario et al., 2020; Picon et al., 2019; Taneja et al., 2020; Zhong and Zhou, 2020). Furthermore, the ML methods were used to address different risk types; (i) production risk, e.g., a self-attention Convolution Neural Network (CNN) for crop leaf disease detection (Zeng and Li, 2020); (ii) Financial risk, e.g., evaluation of insurance risk in case of climate change using different regression models (Lyubchich et al., 2019); (iii) Institutional risk, e.g., principal component analysis for assessment of the seeding policies in East Africa in the face of climate change (Westengen et al., 2019); (iv) Market risk, e.g., a heuristic ML approach for agriculture supply chain risk assessment (Yan et al., 2019); (v) Personal risk, e.g., artificial neural network (ANN), K-nearest neighbors (K-NN), and support vector machines (SVM) methods to evaluate the effects of the pesticides and/or cigarette smoke to farmers' health (Tomiazzi et al., 2019).

In recent years, researchers reviewed the FRM literature from different perspectives, for instance, investigating only one type of risk (Martinelli et al., 2015; Sankaran et al., 2010), focusing on a specific application domain (Boyd and Bellemare, 2020; Duong et al., 2019), reviewing the methods in the literature applied on a particular type of data collected by a specific sensor (Barbedo, 2019; García-Berná et al., 2020), and from a general perspective but not investigating the risk analysis methodology used (Komarek et al., 2020). Hence, the current mapping study is aimed to complement earlier reviews by providing a systematic mapping study to identify and analyze the state-of-the-art advances in machine learning-based farm risk management (ML-FRM). The present paper is the first to adopt the form of a systematic mapping review study in the FRM research domain. A systematic mapping study is conducted by following a structured methodology, in which the objective is to extract current trends in publications, publishers, used methods, applications, weaknesses, challenges, etc., to provide recommendations for researchers and practitioners in the specific field. The key contributions of this paper are as follow; (i) we reviewed the ML-based FRM literature from a holistic farm risk management perspective including risk types and risk components and demonstrate the current trends, and (ii) provide a list of developed ML methods for FRM that can be used either by researchers or practitioners. Furthermore, (iii) we demonstrate the current research directions and the limitations in the use of ML methods for FRM, and accordingly (iv) based on the gap analysis in the literature and the sate-of-the-art ML methods in computer science we provide guidelines on how to further ML can contribute to FRM. Moreover, (v) we provide insights from other disciplines e.g., agro-economic and disaster risk management, for ML-FRM future works.

The remainder of the paper is organized as follows. Section 2 provides background information on machine learning and FRM including the definition of the FRM concept and the related terms. Section 3 gives a step-by-step explanation of the systematic mapping methodology used in this study. In Section 4, the quantitative results of the study are presented and visualized. Subsequently, Section 5 provides the discussions over the results, main findings, challenges, and limitations of the reviewed papers, and finally, Section 6 concludes the paper.

2. Background

2.1. Farm risk management

Risk refers to the degree of uncertainties and/or probability of adverse results on a farm such as lower yields and incomes, farmer health problems, uncertain input/output prices, change in farm-related regulations and policies, or change in the availability of financing sources (Hardaker et al., 2015). Farm risk can be grouped based on two main perspectives: the addressed risk type, and the targeted risk component. Farm risk types can be classified into five main groups (Komarek et al., 2020) as follows: (i) production risk refers to uncertainties in the natural growth process of crops and livestock; (ii) market risk relates to uncertainties in marketing including prices, costs, and market access; (iii) institutional risk focuses on unpredictable policy and regulation developments or changes generated by formal or informal institutions; (iv) personal risk refers to the problems related to individuals that affect the farm or farm household such as human health and personal relationships; (v) financial risk refers to the variability of the general financing sources and the farm's operating cash flow.

In addition, the farm risk management cycle consists of four main components that are linked to the time and aim of the assessment (Fig. 1) similar to what is defined in the field of disaster risk management (Coppola, 2015; UNISDR, 2009). Two are related to pre-event time usually called prevention-mitigation and preparedness, and two are related to post-event time usually called response and recovery. After an

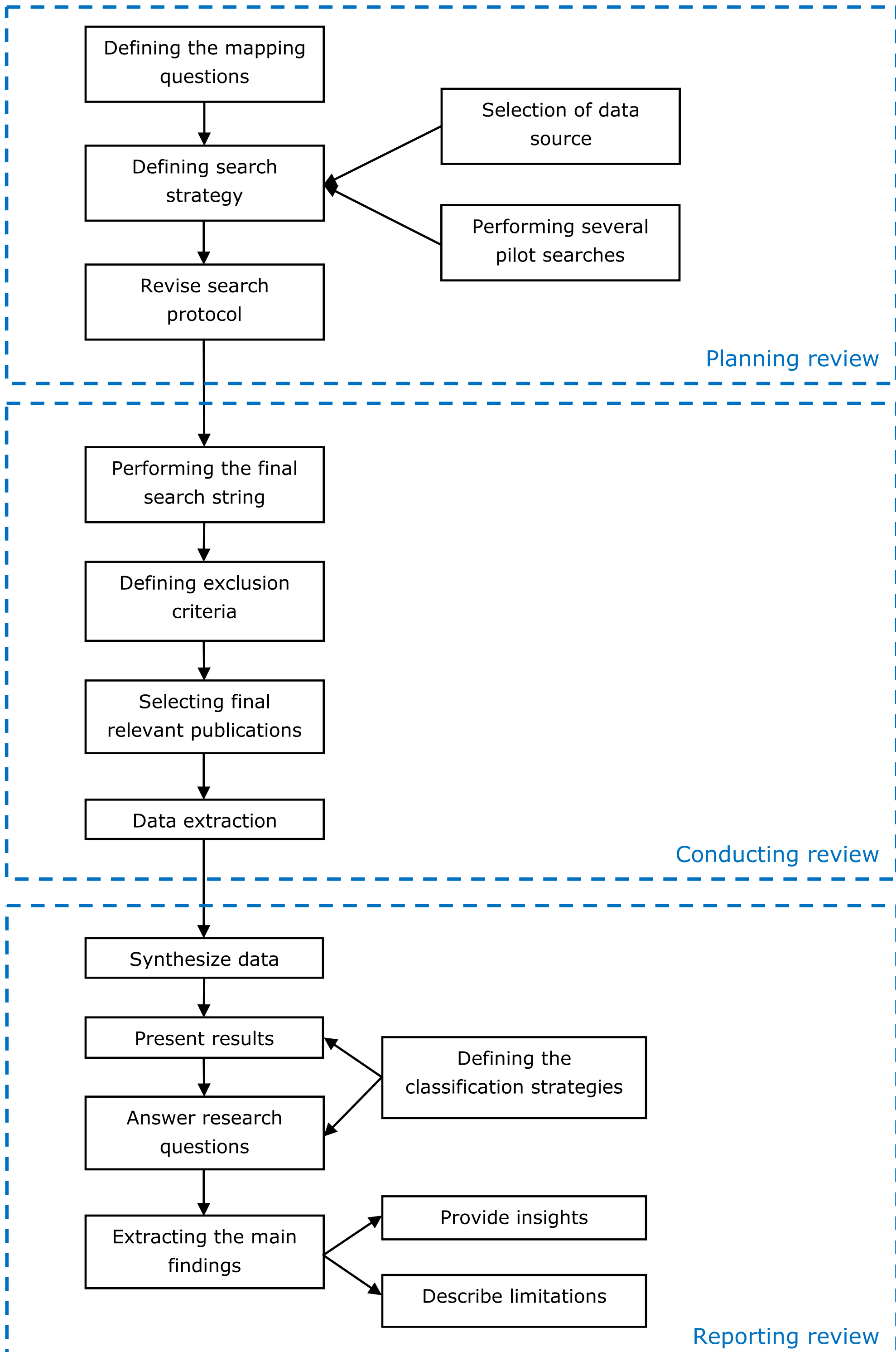

Fig. 2. Mapping review protocol.

adverse event or disturbance, the provision of emergency actions are taken to reduce further impacts (response phase) and then return to a normal condition (recovery phase). In the mitigation phase, actions are taken to prevent an adverse event, reduce its chance of happening, lessening or limitations of the diverse impacts of disturbances and related uncertainties. In the preparedness phase, knowledge and capacities developed by governments, individual farm holders, and other organizations are used to effectively anticipate, respond to, and recover from, the impacts of likely, imminent or current events/disturbances or conditions. To make effective decisions in the response phase, it is necessary to assess the impact of the disturbance by evaluating the damages to the farm (Elahi et al., 2019; Gutierrez et al., 2019; Lee et al., 2018; Yang et al., 2019). In addition, decision-makers making plans in the mitigation and preparedness phases need information regarding the vulnerability and resilience of the farm (Aleksandrova et al., 2014; Ghaffarian et al., 2018; Kantamaneni et al., 2020; Meuwissen et al., 2019) or use models to predict an upcoming event (Marvin and Bouzembrak, 2020; Ribeiro and Coelho, 2020). Vulnerability refers to the inability of a farm and its elements at risk to resist uncertainties or to respond when a disturbance has occurred. While resilience is the ability of a farm exposed to uncertainties or disturbances to resist, absorb, maintain its essential functions and recover from the effects in a timely and efficient manner (Coppola, 2015; UNISDR, 2009). Hence, impact, vulnerability and resilience assessments and damage/impact prediction are crucial for FRM. Each of the explained risk types (e.g., production risk) can be assessed to address any of the risk components, depending on the time and aim of the evaluation by conducting impact, recovery, vulnerability or resilience assessments, and damage prediction. ML methods can contribute to such assessments directly, for example, by assessing impact or damage to the farm (Chen et al., 2020a; Huang et al., 2019), and indirectly by extracting relevant information from available data sets, for example, for vulnerability (Rodriguez-Galiano et al., 2014; Sendhil et al., 2018) and resilience assessments (Chanana-Nag and Aggarwal, 2020; Steward et al., 2018).

2.2. Machine learning

Machine learning is a branch of artificial intelligence, in which computer programs (algorithms) use data to automatically improve themselves through experience and learning. This makes ML suitable to execute different tasks including detection, recognition, and prediction, where historical data exists. The performance of ML models mainly relies on the quality and quantity of the data and the type of the employed algorithms. It is crucial to select the proper algorithm to solve the problem at hand, considering the type and size of the available data. Datasets with high-quality and quantity can mostly increase the accuracy of ML models. In general, two types of data can be used to train ML algorithms: labeled and unlabeled. Labeled data have both input and output information, while unlabeled data have only input information. There are four different ML types based on the ways to train them:

- **Supervised learning:** The computer program is trained on labeled data to develop a function between the input and the output. Manual work is required to produce labeled data. Hence, supervised learning is mainly used where we have enough knowledge regarding the data. In addition, feature engineering (in conventional ML models), parameter tuning and algorithm selection are required to be done by an expert. Supervised machine learning algorithms are employed to address regression and classification tasks. ML algorithms are used to optimize the parameters and minimize the error to predict a continuous outcome value and of the discrete output value (e.g., class) using input variables in the regression and classification tasks, respectively.
- **Unsupervised learning:** Contrary to supervised learning, unsupervised learning uses only unlabeled data. Hence, it does not require manual work. Unsupervised learning is mainly used where we do not have sufficient knowledge regarding the input data to only group them into different patterns. Unsupervised ML algorithms are used to address clustering, data/dimensionality reduction and anomaly detection tasks.
- **Semi-supervised learning:** Using labeled data makes the prediction of ML algorithms more accurate and robust; however, it requires tedious manual work and is an expensive process. Hence, to develop a cost-effective yet accurate model, semi-supervised ML algorithms require only a small portion of the input data as labeled while the majority are unlabeled.
- **Reinforcement learning:** It uses trial and error-based learning and a feedback mechanism to update its previous status and action to optimize the final developed function. Agents are defined in reinforcement learning to observe and take actions in an environment. As the result of their actions, they get some rewards or punishments, and accordingly, update the ML model. This is good for decision making for example to extract optimal policy solutions.

Table 1
Mapping review questions and their rationale for the review process.

ID	Mapping Question	Rationale
MQ1	What publication channels are the main targets for ML-FRM?	Identifying where ML-FRM research can be found, and the most appropriate channels for future studies (i.e., publisher, journals)
MQ2	Which research communities include papers in ML-FRM?	Identifying the research communities (e.g., computer science) contributed to ML-FRM
MQ3	How was the frequency of approaches related to ML-FRM changed over time?	Extracting the publication trends over time to ML-FRM
MQ4	What are the main research types of ML-FRM studies?	Exploring different types of research in ML-FRM in the literature
MQ5	What types of farms are addressed in ML-FRM?	Extracting the most prominent farm types covered in ML-FRM
MQ6	What are the most frequently applied research methods, and how these changed over time?	Extracting the different ML types and methods employed/developed in the literature for ML-FRM
MQ7	What types of data were used for ML-FRM?	Identifying the main types of data/ data sources used for ML-FRM
MQ8	Which components of risk were addressed in ML-FRM?	Studying what are the most frequently tackled components of the risk management cycle in ML-FRM literature
MQ9	Which types of risk were addressed in ML-FRM?	Analyzing what types of risks are mostly studied in ML-FRM research

3. Methodology

The current review study was carried out in the format of a systematic mapping review based on the guidelines provided in Petersen et al. (2015). The aim of a systematic mapping study is to give an overview of a research area through classification and counting contributions in relation to the categories of that classification (Petersen et al., 2015). Accordingly, it differs from a systematic literature review study by investigating relatively broad topics and mainly mapping the structure of a research area rather than digging in details and synthesizing the evidences. This also allows and requires reviewing a larger number of papers in a study. Hence, the purpose of this study is to provide an overview of the use of ML methods in FRM content, identifying the publishers, journals and the quantity of the papers published, active research communities in this topic, and other interesting details accordingly.

3.1. Mapping review protocol

At the start of the study and before conducting the systematic mapping review, a review protocol was developed. This protocol defines the steps and methods for performing the specified systematic mapping study, and consequently, it reduces the research biases (Fig. 2). The developed review protocol consists of three main steps: planning, conducting, and reporting the review. In the first main step, i.e., planning review, we identified the mapping questions (explained in Section 3.2) according to the objective of this study. Subsequently, we defined a search strategy including the search string and data sources after performing several pilot searches and revisions (Section 3.3). In the second step, i.e., conducting review, we implemented the final search string on the selected data source and extracted the final publications based on the defined exclusion criteria (Section 3.4). Then, we used a data extraction strategy to extract the required information (Section 3.5). To do so, we developed a data extraction form that was defined after a pilot study (Appendix A.1). In the final step, i.e., reporting review, we synthesized the extracted data and defined classification strategies to present the results and answer the mapping questions. In addition, we analyzed and extracted the main findings, insights, and limitations of the review.

Table 2
Exclusion criteria for the review process.

ID	Exclusion Criteria
EC1	Papers in which the full text is unavailable
EC2	Papers gathered as a duplicate from different platforms
EC3	Papers that are not written in English
EC4	Papers that are not aiming to directly contribute to FRM
EC5	Papers that do not directly use ML methods
EC6	Papers that do not validate the proposed study
EC7	Papers that provide a general summary without a clear contribution
EC8	Review and editorial papers

3.2. Mapping questions

A total of nine mapping questions (MQs) were defined based on reviewing the papers to detect the most interesting aspects to extract (Table 1). Accordingly, the research and further analysis were built on these questions. The first five questions (MQ1–5) help to extract general information and an overview of where one can find publications related to ML-FRM, the research communities worked on ML-FRM, the frequency of the approaches, the research and farm types of the ML-FRM studies. The rest of the questions (MQ6–9) were defined to extract details and more specific aspects of ML-FRM, such as the ML types and methods and the data types employed, the different risk components and types addressed.

3.3. Search strategy

The initial literature search was done automatically in the Institute for Scientific Information (ISI) Web of Knowledge (Web of Science) using a predefined search string. This database indexes ISI publications, which assure the quality of the studies while covering most of the high-quality publications. The search was conducted in August 2020. When defining the search string to extract relevant papers, a balance needs to be struck between extracting only the most suitable papers, while reducing the possibility of missing any relevant publications. This was ensured by selecting keywords that are usually used in the FRM literature while excluding common terms between different fields. The search query was applied to search in Title, Abstract, and Keywords of the papers. The following text represents the search string that was formulated for the ISI Web of Knowledge database:

((“agri” OR “farm*” OR “crop” OR “livestock” OR “dairy”) AND (“risk” OR “resilien*” OR “damage” OR “impact” OR “recovery” OR “expos*” OR “vulnerability” OR “coping capacity*” OR “disease” OR “adaptive capacity”) AND (“machine learning” OR “deep learning” OR “artificial intelligence” OR “neural networks” OR “CNN” OR “smart” OR “AI”))*

The search string is the combination of three groups separated with “AND”. This means that at least one word of each group is required to appear in Title or Abstract or Keywords of the publications to be selected from the database. The first group corresponds to the subject, including terms to find papers that address any farm type (e.g., crop-based). The second group corresponds to the task, including terms related to any types of risk and its components (e.g., damage). The third group corresponds to methods, including terms to find papers that used any ML method in the study (e.g., deep learning).

3.4. Screening of primary studies

The used search query string has a broad scope (1,819 papers), which is usually the case in systematic mapping reviews (García-Berná et al., 2020; Gurbuz and Tekinerdogan, 2018). Therefore, it ends up with a large number of publications found relevant for the study. In addition, our strategy includes searching the Abstract of the papers, although it ensures any key publications are not omitted, it led to an even more number of papers. Hence, in order to reduce the number of selected papers, we defined exclusion criteria (EC). Papers that meet one or more of these ECs were discarded. This process was applied manually, and reduced the total number of 1,819 papers to 746 papers according to the defined as in Table 2.

3.5. Data extraction strategy

This section explains how MQs can be answered for the selected papers. We created a data extraction form/table to extract relevant information and classified the possible answers for each question using reliable sources available in the literature.

The data extraction strategies to answer MQs developed for the present study are as follows:

- **MQ1.** The publisher and the name of the journal for each paper were identified to answer this question.
- **MQ2.** In order to identify the research communities, we classified the papers based on their published journals' subject area defined in Web of Science. We only considered the main subject areas and finally defined six standard categories as follows: Agriculture, Computer Science, Geosciences and Environmental Sciences, Economy and Business, Social Sciences, and General. Web of Science also provides ranking for the journals based on their impact factors and group them into four quartiles (Q1-4) in each subject area. Accordingly, we used this ranking to assess the quality of the journals in different disciplines. The categories for the papers were selected based on the quality of the journal in the specific discipline, and thus if the journal is a multidisciplinary journal we categorized it based on the subject area in which it has the highest quality. In addition, the general category consists of multidisciplinary journals which have equal qualities for more than one discipline.
- **MQ3.** We extracted the year of each paper and classified them per publication year to extract the publication trends.
- **MQ4.** Studies can be distinguished based on the conducted research types, for example, a paper can propose a new method or it can evaluate an existing one in a new application area. We adapted the classification of the research types proposed by Petersen et al. (2008) for the current study as follows:
  - Evaluation research: Existing ML methods/techniques are implemented and evaluated in practice.
  - Solution proposal: A ML solution/approach is proposed to address FRM. This solution may be a new ML approach or a significant extension of an existing approach. In addition, the performance of the proposed approach should be evaluated and its potential benefits can be determined with an experimental study.
  - Other. Other types of research can include e.g., opinion papers, experience papers, etc.
- **MQ5.** The farm types can be broadly classified into the following groups:
  - Crop-based. The papers that only addressed crop-based FRM using ML approaches
  - Animal-based. The papers that only addressed animal-based FRM using ML approaches.
  - Mixed. The papers that addressed a general challenge related to both growing crops and raising animals, or proposed ML methods that solve a common problem for mixed farms.
- **MQ6.** Another interesting aspect to analyze is the different ML types and methods that are used in the selected papers to address different ML tasks. For this, we classified the papers based on three criteria: used ML types, addressed ML tasks, and employed/developed ML methods. The papers are classified based on the used ML types, as described in Section 2.2., into four categories: supervised, unsupervised, semi-supervised, and reinforcement learning. In addition, the papers are classified based on the addressed general ML tasks as follows: regression, classification, clustering, and data reduction.

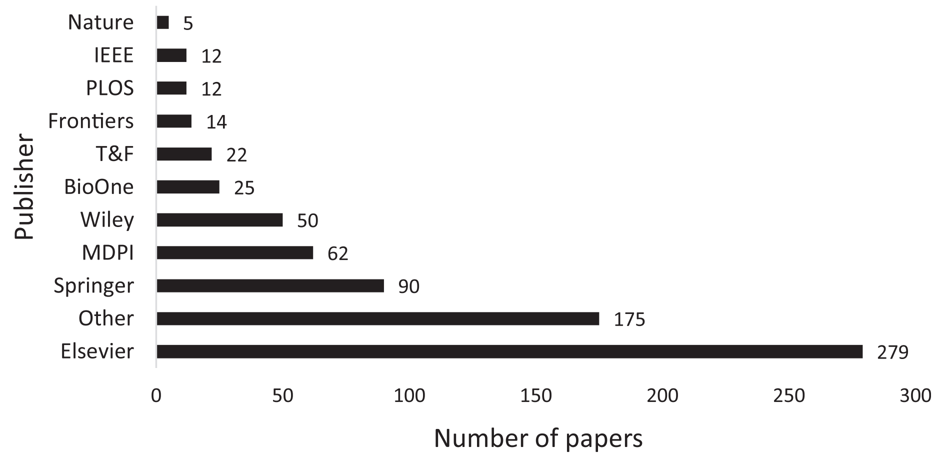

Fig. 3. Publication channels of the selected papers.

There are many different ML algorithms/methods developed in the literature. However, according to the initial screening of the papers and extracting the most frequently used methods, we selected the following methods to classify the papers.

- Regression: includes all types of regression models unless deep learning-based models.
- Support Vector Machines (SVM)
- Ensemble methods (EM): includes any ensemble-based approaches such as Random forests, Boosted methods (e.g., Gradient boosting)
- Bayesian methods: includes any method using Bayesian statistics such as Naive-Bayesian, and Markov random fields.
- Artificial Neural Networks (ANN): including, neural networks, feedforward networks, backpropagation networks, multilayer perceptron method.
- Deep Learning (DL): includes recurrent neural network (RNN), Long and Short Term Memories (LSTM), deep regression modeling, and any deep neural networks.
- Convolutional Neural Networks (CNN): includes any CNN-based approaches.

Fig. 4. Publisher and journal names of the selected papers.

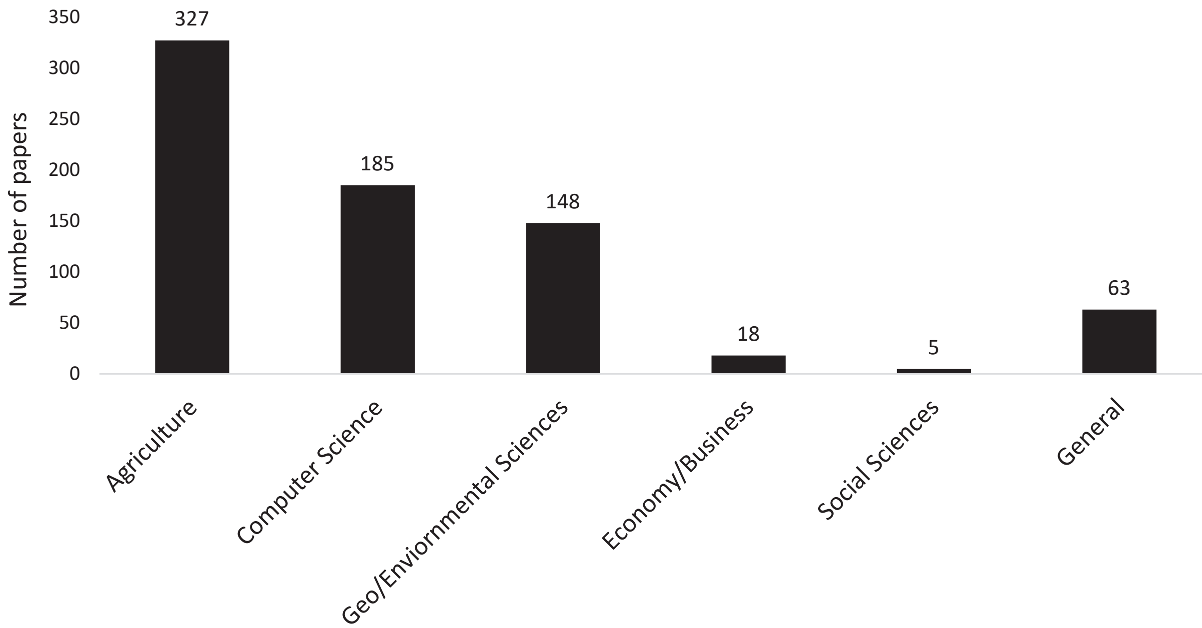

Fig. 5. Research communities of the selected papers.

– Other: includes optimization approaches, decision trees, hybrid methods, fuzzy methods, heuristic methods, k-nearest neighborhood, clustering, Principal component analysis (PCA).

- **MQ7.** The used data types in the selected papers can be classified as follow:

– Visionary sensors data: includes images and videos.
– Non-visionary sensors data: includes any sensory data, for example, sensor data for dairy cows, GPS data to track cow movements.
– Earth data: includes any data related to the earth surface such as hydrological data, and field-based ones such as soil, and water data.
– Field data: includes any types of data based on fieldwork or surveys, for example, yield data.
– Climate data: includes weather, climate, and air quality data.
– Socio-economic data: includes any data associated with the socio-economic status of farm and farm holders, e.g., bank credit data.
– Other: includes any other data e.g., genome data.

- **MQ8.** The selected papers are classified based on the assessment types that addressed different components of the risk as follow:

– Impact: includes papers in which conduct impact and damage assessments.
– Resilience: includes papers that addressed resilience, adapting, coping capacities in FRM content.
– Vulnerability: includes papers that directly mention and tackle vulnerability in Farms.
– General risk/Risk: includes papers that addressed the risk in general without specifically talking about any assessments types and components of risk, for example, extracting different risk factors. The prediction/forecasting studies are in this group.

- **MQ9.** The selected papers are classified based on the risk types according to (Komarek et al., 2020):

– Production risk refers to uncertainties in the natural growth process of crops and livestock.
– Market risk relates to uncertainties in marketing including prices, costs, and market access.
– Institutional risk focuses on unpredictable policy and regulation developments or changes generated by formal or informal institutions.
– Personal risk refers to the problems related to individuals that affect the farm or farm household such as human health and personal relationships.
– Financial risk refers to the variability of the general financing sources and the farm's operating cash flow.

3.6. Synthesis

After selecting the papers and performing the data extraction based on the defined mapping questions the last step is synthesizing the results. For each MQ, the papers are grouped into the defined classes, counted for each of which groups, and accordingly visualized in charts or presented in tables. Then, the results are discussed in detail and finally, a narrative summary bolds the main findings of the mapping study.

4. Results

A total number of 1,819 papers were extracted using the search query from the ISI Web of Knowledge database as explained in Section 3.3. Then, 746 papers were selected using the defined nine exclusion criterion. Therefore, the final selected papers were employed to obtain the results by classifying them according to the defined MQs. The results are presented in the following subsections.

MQ1: What publication channels are the main targets for ML-FRM?

To answer this question we classified the papers based on their publishers and journals. Fig. 3 shows the publisher names with at least five published papers in ML-FRM, and the other class is the sum of the publishers with less than five papers. Most of the ML-FRM papers are published in the Elsevier journals with 279 number of papers (Fig. 3). Springer and MDPI are the second and third most published ML-FRM papers with 90 and 62 papers, respectively.

Fig. 4 shows the names of the journals with at least five papers published in ML-FRM, and the total number of papers. An interesting observation is that although Springer has 90 publications in ML-FRM, it does not have a journal with 5 or more papers published on this topic.

MQ2: Which research communities include papers in ML-FRM?

Fig. 5 shows the number of papers published by different research communities. The agriculture research community has published the most in the ML-FRM.

MQ3: How was the frequency of approaches related to ML-FRM changed over time?

For this mapping question, we illustrate the number of annual

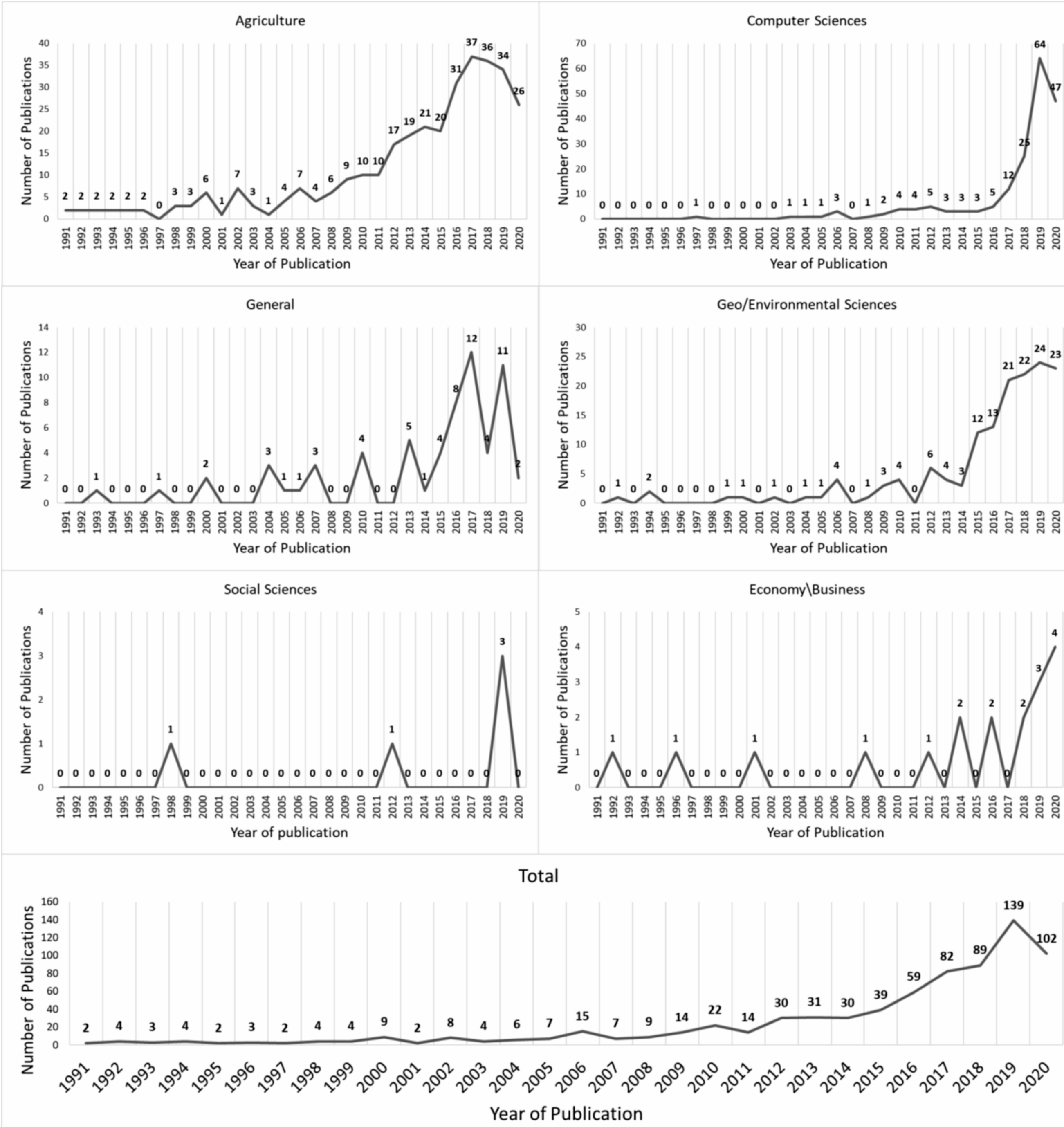

Fig. 6. The number of annual publications on ML-FRM for different research communities and in total.

publications as well as their associated research communities per year until August 2020 (Fig. 6). The chronological overview of the publications shows an increasing trend in ML-FRM studies, which continued in 2020 considering that the search from the online database was conducted in August 2020. In addition, the rate of increase in the number of publications of the computer science research communities is higher than the others.

MQ4: What are the main research types of ML-FRM studies?

The selected papers were grouped into three standard categories: evaluation research, solution proposal, and other. Most of the papers are evaluation research (52%), and almost one-third of the papers are solution proposals (38%), and the rest are in the other category (10%) (Fig. 7).

MQ5: What types of farms are addressed in ML-FRM?

Table 3 shows the farm types addressed in the selected papers with their corresponding number of publications. The crop-based farm is the most addressed farm type in the literature with 459 papers, while 247 papers address the animal-based farm and only 40 papers studied mixed farm types in one research.

MQ6: What are the most frequently applied research methods, and how these changed over time?

Fig. 8 shows the used ML types for FRM. Supervised learning is predominantly used in the literature to address ML-FRM with 740 papers (Hepworth et al., 2012; Wang et al., 2020; Wu and Xu, 2019), while unsupervised learning (Kumar et al., 2019a; Liu et al., 2010; Lu et al., 2017) and reinforcement learning (Govindan and Al-Ansari, 2019) types

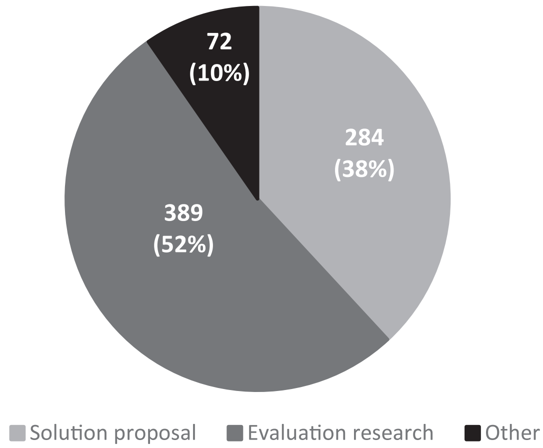

Fig. 7. Research types of the selected papers in ML-FRM.

Table 3
The types of farm addressed in the literature.

Farm type	Example references	Number of papers
Crop-based	(Ali et al., 2018; Calou et al., 2020; Chavez et al., 2015; Ghielmi and Eccel, 2006; Lee et al., 2020; Lie et al., 2019; Messier et al., 2019; Perez-Bueno et al., 2016; Ribeiro and Coelho, 2020; Westengen et al., 2019)	459
Animal-based	(Ahmad, 2009; Bates and Saldias, 2019; Dalanezi et al., 2020; Domun et al., 2019; Fourichon et al., 2001; Miekley et al., 2013; Nasirahmadi et al., 2020; Vasquez et al., 2019; Wagner et al., 2020; Zaborski et al., 2016)	247
Mixed	(Aryal et al., 2020; Chandra et al., 2017; Dang et al., 2020; Goyol and Pathirage, 2018; Gyamerah et al., 2019; Jost et al., 2016; Kumar et al., 2019a; Lyubchich et al., 2019; Roberts and All, 1993; Strzepek et al., 2013)	40

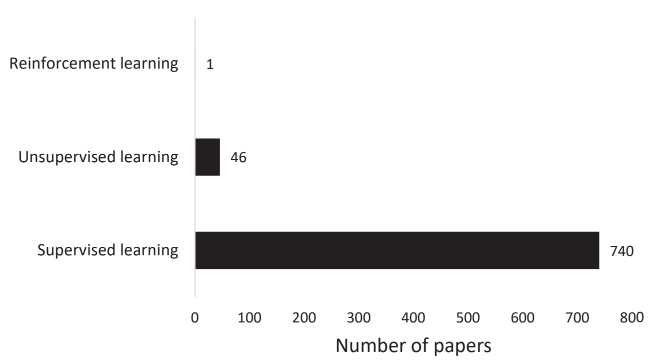

Fig. 8. The used ML types for FRM.

are used in 46 and 1 papers. In addition, the most frequently addressed ML tasks are regression (Ebrahimie et al., 2018; Garcia-Ispierto et al., 2007; Smith et al., 2009) and classification tasks with 511 and 230 papers, respectively (Fig. 9). Clustering (Alzoubi et al., 2017; Lu et al., 2017; Viet et al., 2012) and data reduction (Kumar et al., 2019a, 2019b; Martinez-Martinez et al., 2018) tasks are also addressed in 29 and 17 papers, respectively.

Tables 4 shows the employed ML-based methods for FRM, and Fig. 10 shows the chronological overview of the used/developed methods. The most frequently used method is regression modeling (352/746), which was mostly employed to extract the relation between risk and the targeted variables/factors in farms (Andriamanivo et al., 2012; Marko et al., 2016; Smulski et al., 2020; Vadlejch et al., 2014). In recent years, there is a significant increase in the number of papers that used/developed CNN-based methods, which are mostly focused on detecting diseases in crops (Karthik et al., 2020; Kim et al., 2020; Zeng and Li, 2020), dairy farm (Sun et al., 2019), pig farm (Li et al., 2019; Marsot et al., 2020), and pest detection (Cheng et al., 2017; Xing et al., 2019) and weed detection (Espejo-Garcia et al., 2020; Sa et al., 2018). On contrary, other deep learning methods were only used in 21 papers, which mostly focused on animal-based farm disease detection (Domun et al., 2019; Plekhanova et al., 2019), despite the recent improvements in computer facilities that have enabled performing the computationally expensive methods like CNN.

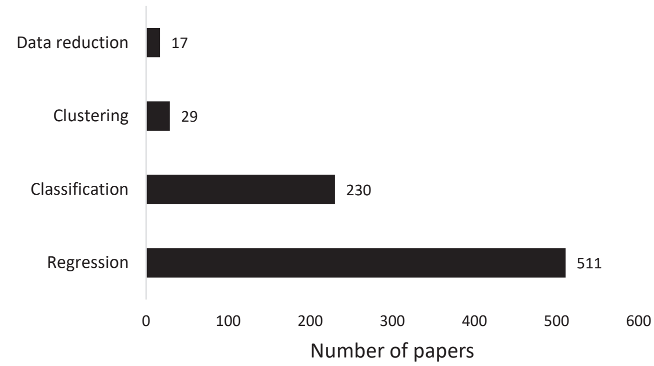

Fig. 9. The addressed general ML tasks in ML-FRM.

Table 4
The ML methods used in the selected papers for FRM.

ML method	Example references	Number of papers
Regression	(Aungier et al., 2014; Capitani et al., 2019; Garcia-Ispierto et al., 2007; Gompo et al., 2020; Waltner et al., 1993)	352
ANN	(Alzoubi et al., 2019; Aparecido et al., 2019; Avila-George et al., 2018; Hernandez et al., 2020; Martinez-Martinez et al., 2018)	96
Bayesian	(Benitez et al., 2017; Marvin and Bouzembrak, 2020; Meisner et al., 2016; Viet et al., 2012; Willett et al., 2016)	12
SVM	(Calou et al., 2020; Griffel et al., 2018; Machado et al., 2019; Mudereri et al., 2020; Zhuang et al., 2018)	44
EM	(Chen et al., 2020b; de Castro et al., 2020; Hermans et al., 2017; Taneja et al., 2020; Yazdanbakhsh et al., 2017)	55
DL	(Ebrahimi et al., 2019; Espejo-Garcia et al., 2019; Fan and Xu, 2020; Ghahari et al., 2019; Zhao et al., 2019)	21
CNN	(Karlekar and Seal, 2020; Marsot et al., 2020; Picon et al., 2019; Sladojevic et al., 2016; Wang et al., 2018)	95
Other	(Leroy et al., 2018; Lins et al., 2020; Miekley et al., 2012; Walsh et al., 2018; Wang et al., 2020)	71

MQ7: What types of data were used for ML-FRM?

Fig. 11 shows the most frequent types of data used in ML-FRM studies. Field data which are based on fieldwork is the mainly used type of data in the studies; however, they are gradually being replaced by other automatic data collection methods e.g., using sensors (visionary or non-visionary). Visionary sensors data are collected from different sources such as video cameras (Fang et al., 2020), mobile phone images (Petrellis, 2019), drone/Unmanned Aerial Vehicle (UAV) data (Su et al., 2018), satellite images (Santoso et al., 2019) are the second most used data sources for ML-FRM, and is increasing by advancing in technologies that ease collecting such data. Non-visionary sensors (Smith et al., 2020; Tamura et al., 2019), earth (Arshad et al., 2013), climate (Funk et al.,

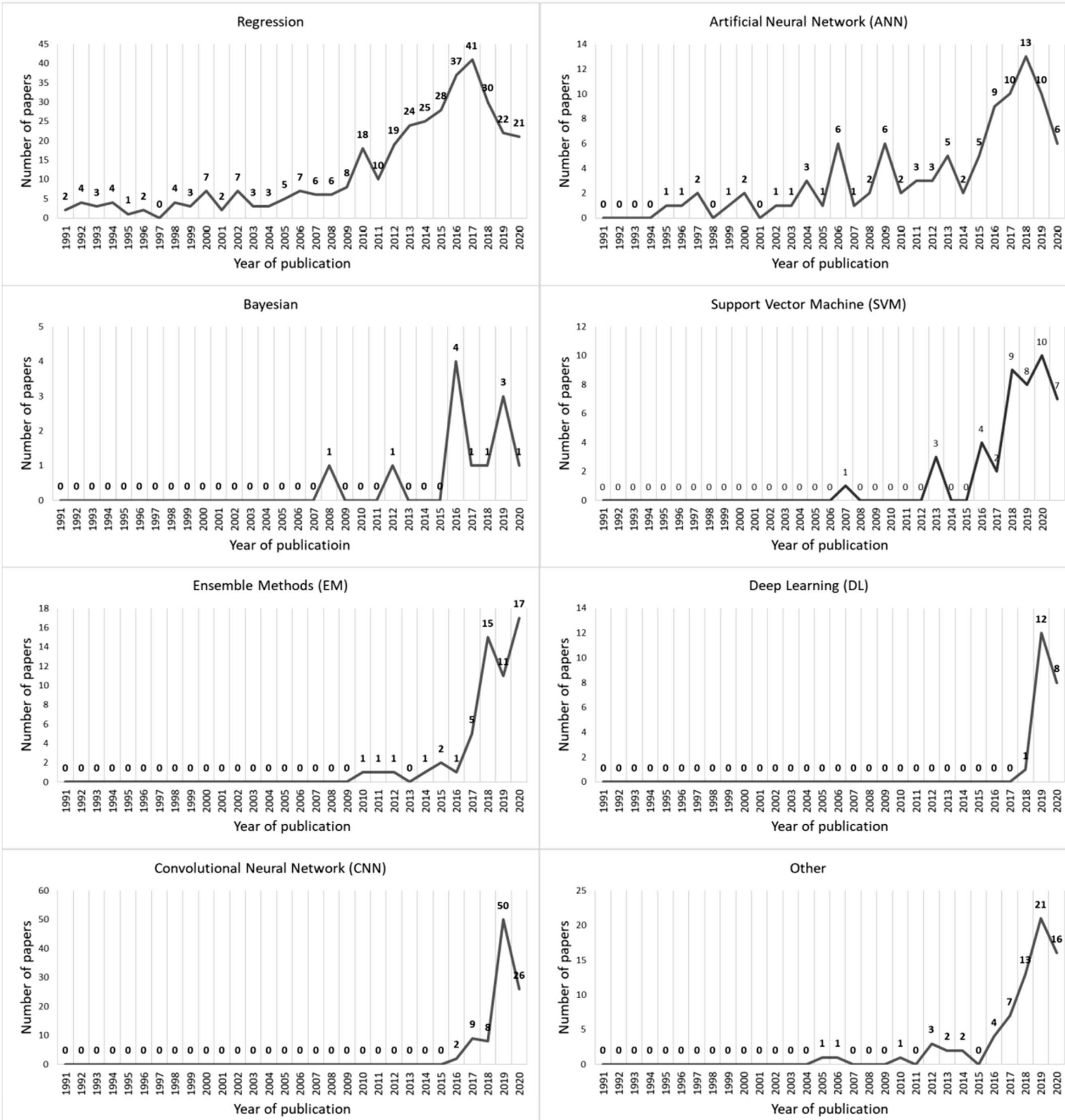

Fig. 10. The number of annual publications on ML-FRM classified by the employed/developed ML methods.

2014), and other (Mochida et al., 2015) data types also employed for ML-FRM. The socio-economic data is the least used data type in ML-FRM (Kakhki et al., 2019; Pal et al., 2016) which is primarily employed in combination with other data types (Arndt et al., 2014; Chen et al., 2020b).

MQ8: Which components of risk were addressed in ML-FRM?

Almost two-thirds of the selected papers address the FRM from a general perspective e.g., finding the effect of targeted variables on risk (e.g., production) without mentioning or focusing on a specific risk component. The impact assessment was investigated in 248 papers from the selected papers, in which most of them detected disease (Shakoor et al., 2017) or damage (Avila-George et al., 2018). On the other hand, only 35 and 11 of 746 papers studied farm vulnerability and resilience (Table 5). However, risk mitigation and reduction need pre-event/impact assessment that is possible through evaluating farm vulnerability and resilience.

MQ9: Which types of risk were addressed in ML-FRM?

Table 6 depicts risk types studied in the selected papers with the exact number of papers and example references. Accordingly, the production risk is the most studied risk type in the selected papers covering 96% of the papers. In addition, financial, institutional, personal and market risks were studied in 13, 11, 8, and 2 papers, respectively. Table A1.

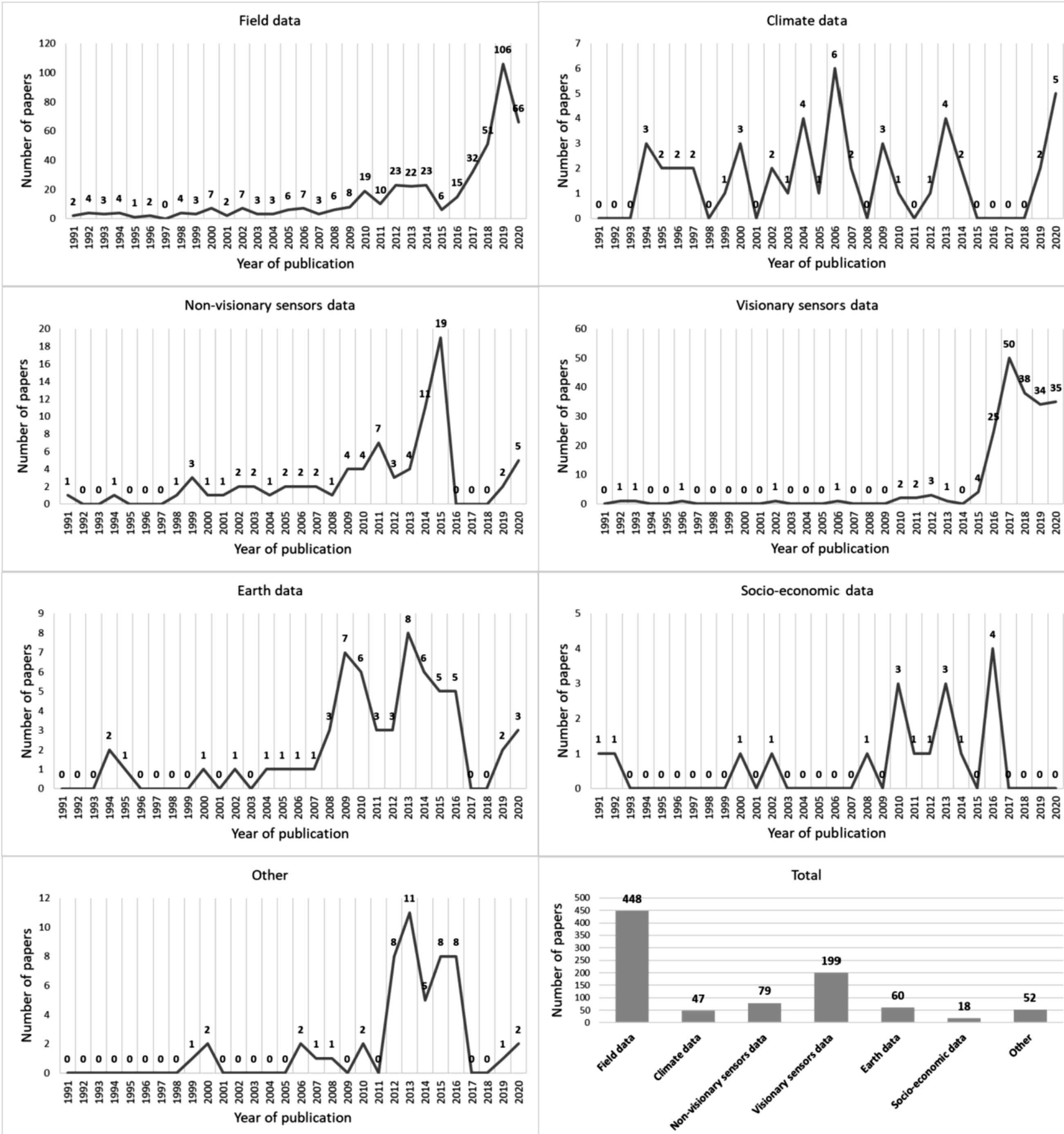

Fig. 11. The number of annual publications on the employed data for ML-FRM and in total.

5. Discussion

The main objective of this study is to provide an overview of the state of the research in the use of ML for FRM by answering the defined nine mapping questions. In this section, we discuss the presented results and findings of this study to provide insights towards future research. In addition, the limitations of the mapping study are discussed.

5.1. Main findings

The major findings that can be extracted from the presented results are as follows:

- The main target publisher for the ML-FRM studies is Elsevier journals. In addition, the "Computers and Electronics in Agriculture" journal and 'Journal of Dairy Sciences" published the largest number of papers in crop- and animal-based FRM, respectively. However, there are plenty of publishers and journals that have papers published on ML-FRM (i.e., the selected papers are published in 362 different journals) which shows the potential of the subject and the need to be addressed from various perspectives and disciplines.
- Recently, the FRM topic has gained increasing attention in the computer science research community, which helped to increase in developing and using more advanced ML methods. However, most of them address computer vision-based problems for example to detect disease (Wang et al., 2017), weed (Sharpe et al., 2019) and damages

Table 5
The assessment types that addressed different risk components in the selected papers.

Risk component	Example references	Number of papers
Impact	(Busin et al., 2019; Chen et al., 2020a; Huang et al., 2019; Markom et al., 2009; Mohanty et al., 2016)	248
Vulnerability	(Douxchamps et al., 2016; El Yacoubi et al., 2019; Mudereri et al., 2020; Rodriguez-Galiano et al., 2014; Sendhil et al., 2018)	11
Resilience	(Chanana-Nag and Aggarwal, 2020; Makate et al., 2016; Salack et al., 2015; Steward et al., 2018; Tesfaye and Seifu, 2016)	35
General risk	(Ealy et al., 1994; Jensen et al., 2020; Kaundal et al., 2006; Partel et al., 2019; Sun et al., 2019)	451

Table 6
The type of risks addressed in the selected papers.

Risk type	Example references	Number of papers
Production	(Chaudhary et al., 2016; Esgario et al., 2020; Fang et al., 2020; Fuentes et al., 2017; Pydipati et al., 2005)	717
Financial	(Liu and Zhan, 2019; Lyubchich et al., 2019; Muller, 2000; Pinheiro et al., 2016; Zhong and Zhou, 2020)	13
Institutional	(Espejo-Garcia et al., 2019; Lyubchich et al., 2019; Musshoff and Hirschauer, 2014; Strzepek et al., 2013; Westengen et al., 2019)	11
Personal	(Chandra et al., 2017; Elahi et al., 2019; Khatri-Chhetri et al., 2020; Tomiazzi et al., 2018; Tomiazzi et al., 2019)	8
Market	(Chen et al., 2020b; Yan et al., 2019)	2

(Huang et al., 2016). In contrary, although the Agriculture research community has the largest number of papers published in FRM, traditional ML methods (e.g. conventional regression modeling) is the most popular one. Computer scientists mostly focused on developing computer vision-based methods since they need field experts to introduce new/actual field problems in FRM. On the other hand, lack of advanced ML knowledge in field scientists limit them in developing advanced methods. Those depict the need for multidisciplinary works to aggregate the power of different disciplines in developing advanced ML methods to overcome the challenging issues on FRM.

- ML-FRM gains increasing attention due to advances in automatic sensor-based data collection and providing big data for several farm management issues as well as risk management. In particular, the rapid increase in the number of publications in ML-FRM started after a drop in 2011. In recent years, there is a transition from regression analysis to DL-based approaches including CNN-based methods, which will continue as a result of advances in technologies e.g., computer facilities. With entering the different research communities to FRM studies, the increasing interest in ML-FRM is expected to continue in near future.
- More than half of the papers are evaluation research that implements available ML methods for different case studies. While almost one-third of them are solution proposals. This can be due to two main reasons: 1- At least in some specific topics the research community reached maturity and they only try to develop methods to obtain more accurate results for existing problems (e.g., disease detection), 2- In some specific topics with entering the computer science society and providing advanced knowledge of ML methods they provide more advanced and precise methods for existing problems while they cannot identify the untouched problems in FRM subject. Having a detailed look at the selected papers, it can be figured out the second reason is mostly the case in ML-FRM studies, for example, crop disease detection. However, only recently DL-based methods have started to be used in animal-based farm management for example for behavior recognition (Li et al., 2019). The rapid increase in developing advanced ML methods (i.e., DL-based approaches) will continue increasing the evaluation studies to provide accurate solutions for existing problems.
- Regression modeling is still the most used method due to its easy implementation and providing sufficiently accurate results e.g., to find the relations between different risk factors in farm management issues (Aungier et al., 2014). However, the traditional regression modeling can be replaced by other ML methods like SVM and EM and more recently DL in most cases to achieve accurate results, which is already done in a few studies (Romero et al., 2020). The rapid increase in using DL, in particular, CNN approaches is due to the increase in the number of image acquisition platforms such as drones, satellites, mobile phones, and their high resolution.
- Field data are going to be replaced by new platforms/sensors to collect data. For example, aerial and ground image and video capturing sensors for crop and animal disease detection, wireless and other non-visionary sensors for dairy farm production, and climate data. In the meantime, new sensors will serve new types of data which will need new methods or adaptations of existing methods to process and address FRM topics.
- The DL-based methods, including CNN, are mainly used in crop-based farms. However, they can also be used in animal-based farm risk management to increase the accuracy of the results. As a straightforward example, both crop- and animal-based FRM need computer vision-based methods to do disease detection; that means in some cases the developed methods in crop-based FRM can be interchangeably employed for animal-based FRM with some adaptations.
- There is a need to focus and develop ML methods to address all risk components such as recovery, mitigation and preparedness through resilience, vulnerability and recovery assessments rather than only impact assessments. In addition, it is observed that the researchers prefer to use the general term "risk" instead of a term that depicts the more detailed task in their study. Although the use of the term risk is correct since it covers all the risk components, the overuse of this term makes it difficult to find relevant studies. Some of the concepts such as resilience and vulnerability are more recently developed in the risk literature and for this reason, those were specifically addressed in the paper later. For example, farm vulnerability and resilience assessments have been entered to the ML-FRM literature from 2014. In future studies in ML-FRM, it is needed to elaborate more on the targeted risks which in the meantime can lead to unifying the studies and even help to accelerate and simplify the using ML methods for FRM. CNN methods have been mainly used for impact, damage, and disease detection in farms. However, DL, in particular CNN, can also be employed to address other risk components, similar to how it has been used in the disaster risk management field, through recovery (Ghaffarian et al., 2019), vulnerability (Saha et al., 2021) and resilience assessment (Ghaffarian et al., 2018).
- Although assessing production risk is an important task in FRM, other risk types such as financial and institutional risks should be addressed as well. For instance, price volatility may lead to financial uncertainty and risk to farms, which has been on the increase since 2005 (Tropea and Devuyst, 2016). One of the reasons for such a big difference between the number of papers that address production risk and the others is the current challenges in employing/adapting ML methods for social, economic, and policy-based tasks (Athey, 2018). However, interesting examples of using ML methods for such tasks are provided in this study (Espejo-Garcia et al., 2019; Lyubchich et al., 2019; Tomiazzi et al., 2019; Zhong and Zhou, 2020) that can be used to provide insights for future studies.

- It is observed that most studies are aimed to monitor the status of the farm focusing on one or multiple risk types, providing information for making decisions by farmers. However, machine learning, in particular reinforcement learning, has the capacity to make decisions as well, which can be used to optimize risk mitigation (Govindan and Al-Ansari, 2019). Furthermore, reinforcement learning has several applications in economy and finance, for example, to extract optimal policy solutions and to solve complex behavioral problems (Charpentier et al., 2020), which can be also adopted for FRM applications.

5.2. Threats to validity

The main threats to validity of our review are discussed as follows:

Construct validity: The aim of this study is to review the existing literature on the use of ML methods for FRM addressing different risk types and components and provide insights accordingly. To do so, we used an automated search query applied on the ISI Web of Knowledge website (Web of Science). Using this database as the only source of publications may lead to missing other relevant publications that are not included in this study. However, this study aimed to provide an overview of high-quality publications. Hence, indexing in an ISI journal is an accepted way that we used to find and extract the relevant high-quality papers. Excluding non-English papers and the ones that we could not find their full text may also bias the results. However, since the total number of papers that are excluded according to these criteria are not more than 10 papers, they do not have remarkable impact on the final results of this study (considering that the initial number of selected papers was 1819). In addition, there might be missing terms that may impact the final result. However, we tried to keep the search broad, and we refined the search query several times to reduce the possibility of missing any relevant study. Hence, the impact of missing any relevant papers in the final results is low.

Internal validity: We formulated the mapping questions to investigate and extract all the required elements for ML-FRM. Since the mapping questions are based on the precisely defined and explained ML methods, risk types, risk components and other necessary information, the findings of this study are properly described and linked to the extracted results.

External validity: This study reviewed the publications which employed ML methods for FRM. There are other ML methods that are not discussed in this study. However, we provide insights from computer science domain regarding the potential of ML methods for FRM, giving examples of advanced ML methods that can contribute to FRM.

Conclusion validity: We conducted the review based on the accepted structure and protocol for systematic mapping studies (Petersen et al., 2015). Accordingly, the mapping questions, search strategies, screening criteria, and result evaluations are designed and performed based on the widely used structure. In addition, we provided the search string, and data extraction form in the paper, and the extracted publications in an open-source platform. Thus, the results of this study are simply reproducible.

6. Conclusions

This article surveyed the studies and advances in the use of machine learning (ML) for farm risk management (FRM) in the form of a systematic mapping study. Our main goal was to investigate and identify the application domains, trends, current challenges, and limitations of using ML methods for FRM, and accordingly, provide insights and guidelines for future works. As the results of our initial search in the ISI Web of Knowledge, we identified 1,819 studies in ML-FRM, then we selected 746 papers based on the defined exclusion criteria. Involving such a large number of papers in the study allowed us to produce reliable results and extract trends and the research directions in an accurate manner. However, further investigations and studies are required, for example, in a systematic literature review format, to perform detailed analysis and extract advances in different ML methods, in particular deep learning, addressed different risk types and components in FRM. In addition, there is a need to tackle FRM from a different point of view by investigating and extracting what is needed from a data-driven perspective to counteract risks for example, by decreasing the vulnerability and improving resiliency. Even though various types of risks are studied, we observed dominance of production risk-centered studies, a trend in line with the general field of FRM (Komarek et al., 2020). Due to improvements in data acquisition platforms/sensors (e.g., satellites, drones, ground sensors) collecting production-based data has been easier compared to other risk types. Future research should explore other types of risk and could also leverage ML to explore the relationship between risk types such as business risk and financial risk (de Mey et al, 2014). Although it is important to update the status of the farm after exposure to an adverse event, risk mitigation and preparedness analysis through resilience and vulnerability assessments are crucial to reduce and mitigate the impacts and reach the food and agriculture-related sustainable development goals. This issue can be overcome by getting insights from adjacent research fields such as disaster risk management and performing a resilience analysis (Slijper et al., 2021), or widening the scope of analysis to an agricultural systems analysis (Meuwissen et al., 2019). In addition, we observed that most of the DL (e.g., CNN) methods are employed/developed to address crop-based agricultural problems; however, some of them can be easily adopted for animal-based agriculture problems. In recent years, only a few studies used ML methods to address financial, institutional, personal, and market risk analysis. The open challenges and limitations in AI/ML field, including trustworthy, ethical and social impacts, are one of the reasons limiting using ML methods for FRM. We identify a clear scope for data integration and analytical efforts to use ML methods to undertake FRM in these domains.

Table A1
Data extraction form.

#	Extraction element	Contents
General information		
1	ID	Unique ID for the study
2	Title	Full title of the article
3	Authors	The authors of the article
4	Year	The publication year
5	Publisher name	The publisher name (e.g., Elsevier)
6	Journal name	The journal name (e.g., Journal of Dairy Science)
7	Research community	☐Agriculture ☐Computer Science ☐Geosciences and Environmental-Sciences ☐Economy and Business ☐Social Sciences ☐General
Study description		
8	Main objective of the study	
9	Details about the study	E.g., task details
10	Directly address FRM	☐Yes ☐ No
11	Research type	☐Evaluation research ☐Solution proposal ☐Other
12	Farm type	☐Crop-based ☐Animal-based ☐Mixed
13	Machine learning types	☐Supervised ☐Unsupervised ☐Semi-supervised ☐Reinforcement learning
14	Machine learning tasks	☐Regression ☐Classification ☐Clustering ☐Data reduction
15	Machine learning method	☐Regression ☐SVM ☐EM ☐Bayesian ☐ANN ☐DL ☐CNN ☐Other
16	Data type	☐Visionary sensors data ☐Non-visionary sensors data ☐Earth data ☐Field data ☐Climate data ☐Socio-economic data ☐Other
17	Risk component	☐Impact ☐Resilience ☐Vulnerability ☐General risk
18	Risk type	☐Production risk ☐Market risk ☐Institutional risk ☐Personal risk ☐Financial risk
19	Additional notes	E.g., the opinions of the reviewer about the study

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Data extraction form

See Table A1.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2021.106631.

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