Italian Journal of Agronomy
A Journal of Agroecosystem Management
Official Journal of the Italian Society for Agronomy

A scoping review of side-dress nitrogen recommendation systems and their perspectives in precision agriculture

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Keywords: Fertilization; fertilizer amount; sensors; empirical models; mechanistic models; data fusion

Funding: this research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Martina Corti holds a post-doc grant from Università Degli Studi di Milano.

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the final one. Please cite this article as doi: 10.4081/ija.2021.1951

Abstract

A scoping review of the relevant literature was carried out to identify the existing N recommendation systems, their temporal and geographical diffusion, and knowledge gaps. In total, 151 studies were identified and categorized. Seventy-six percent of N recommendation systems are empirical and based on spatialized vegetation indices (73% of them); 21% are based on mechanistic crop simulation models with limited use of spatialized data (26% of them); 3% are based on machine learning techniques with integration of spatialized and non-spatialized data. Recommendation systems started to appear worldwide in 2000; often they were applied in the same location where calibration had been carried out. Thirty percent of the studies use advanced recommendation techniques, such as sensor/approach fusion (44%), algorithm add-ons (30%), estimation of environmental benefits (13%), and multi-objective decisions (13%). Some limitations have been identified. Empirical systems need specific calibrations for each site, species and sensor, rarely using soil, vegetation and weather data together, while mechanistic systems need large input data sets, often non-spatialized. We conclude that N recommendation systems can be improved by better data and the integration of algorithms.

Introduction

From the late ’90s until now, precision agriculture has come to farmers’ attention due to its potential for decreasing economic and environmental costs (Pattey et al., 2001) by applying techniques that increase input use efficiency. Since then, attention has been focused on nitrogen (N), an important growth limiting factor, the management of which can have important economic and environmental drawbacks (Olfs et al., 2005). There are different definitions of precision nitrogen management; one involves the concept of precision crop management that applies nitrogen inputs to match the spatial and temporal variability of crop requirements (Taylor and Whelan, 2005). Precision management is based on two steps: the first involves capturing the variability of soil and crop properties (monitoring); and the second is a decisional level where the pieces of information coming from the monitoring phase are used together to quantify the agronomic inputs to apply. So far, the scientific literature has dealt with the monitoring phase by studying proximal and remote sensing techniques suited for crop and soil monitoring (Mulla 2013), and by evaluating their capacity to estimate N-related crop variables (Corti et al., 2018; Corti et al., 2020). Regarding the second step (decision level), various attempts have been developed to define N recommendation systems assisted by new technologies (Shanahan et al., 2008; Franzen et al., 2016).

Various recommendation systems have been proposed from the late 1990s until now. Not all of them explicitly address field spatial variability, but are worth considering because they estimate recommended N rates for arable crops. Some of these systems have actually been used in operational conditions, such as the N mass balance model (Stanford, 1966) that relies on soil measurements together with weather and crop management information (without in-season monitoring); or commercialized algorithms that imply the use of optical sensors to retrieve crop status (Francis and Piekielek, 1999; Raun et al., 2005; Holland and Schepers, 2010) and make recommendations for N mineral fertilizers. Scientific reviews currently available on this topic are rather specific, because they focus on the approaches used in selected countries (*e.g.,* Morris et al., 2018) or specifically assess methods based on crop sensors only (Shanahan et al., 2008; Franzen et al., 2016). However, no review has yet to summarize the state of the art of N recommendation systems.

Therefore, we carried out a scoping review with the aim to: identify, summarize and review the N recommendation systems available and their geographical and temporal diffusion; define trends of the development and application of these systems over time; and identify knowledge gaps. The review, which involved the analysis of 354 scientific papers published between 2000 and 2020, was carried out following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR; Tricco et al., 2018). This technique allows mapping available evidence on a topic and identifying the main concepts and knowledge gaps.

Four questions were established at the start of the bibliographic research and used as a guide: 1) what recommendation systems are available to support the decision to side-dress N rate at the field and sub-field scale in arable crops? 2) what are the temporal and geographical diffusion of these methods?

3) what advanced solutions can be identified in N recommendation systems? 4) what are the knowledge gaps that limit the adoption of these systems?

This paper describes the literature search and its results, and discusses the knowledge gaps identified.

Materials and methods

This work applied a scoping literature review according to the PRISMA method. Figure 1 summarizes the search flow of our work. Five steps were carried out to answer the research questions, according to the PRISMA method (Tricco et al., 2018): definition of search strategy, titles and abstract screening, definition of eligibility criteria, selection of the studies and data collection, and data charting. Each step is presented in the following sub-sections.

Search strategy

We identified publications in two steps. First, we searched scientific publications in Google Scholar, Scopus, and Web of Science using keywords defining agronomic recommendations ("decision support systems", "decision support tools") in combination with keywords describing nitrogen-related topics ("nitrogen uptake", "nitrogen status", "nitrogen fertilization"), crop monitoring ("remote sensing", "crop monitoring", "soil monitoring") and modelling ("crop modelling", "crop model", "soil model"). Second, we collected papers written by authors and research groups identified during step one, as well as relevant references cited in papers selected in step one. No time limits were imposed. All the publications found were collected in a unique database.

Titles and abstracts screening

A total of 354 publications (journal papers, conference papers, articles in trade journals, factsheets, reports, theses, and patents) were collected. Firstly, the publications were analyzed by type and 17 patents were excluded. The remaining 337 publications were analyzed by reading their abstracts. After the abstract screening, 71 publications were eliminated, because they included qualitative and descriptive reviews of crop monitoring and precision agriculture techniques (n=33), informative articles (n=3), book chapters (n=7), operational manuals (n=5), and publications related to precision agriculture in general (n=23).

Eligibility criteria

After title and abstract screening, the publications considered for eligibility were 266. The full-text papers were then read and evaluated against the eligibility criteria that a paper should either describe a nitrogen recommendation system or propose an advanced solution to estimate an N-related variable. Following this screening, 108 publications were excluded.

Selected studies and data collection

The publications that passed the eligibility criteria were 158. Each publication was classified following the scheme in Table 1.

After the full-text reading of the selected publications and their classification, the database contained 171 records (some publications studied more than one method): 105 records, coming from 91 publications, describing nitrogen recommendation systems; 46 records from 44 publications describing recommendation systems and advanced solutions; and 20 records from 20 papers only describing advanced solutions.

Data charting

The information collected in the database was used to answer the research questions. To this aim, data were summarized in tables and figures using Microsoft Excel (2016) and QGIS (3.16 version; QGIS.org, 2021). Data were reported both as the absolute numbers of records and as percentages compared to the total.

Results and discussion

This section is divided in four sub-sections, each representing one of the research questions established at the beginning of the work.

What nitrogen recommendation systems are available to support the deciding of side-dress nitrogen rate at the field and sub-field scale in arable crops?

<u>Algorithms used in nitrogen recommendation systems and their inputs</u>

The breakdown of the dataset according to the type of algorithms used in the recommendation systems is shown in Table 2.

Empirical models, representing 76% of the dataset, define N recommendations based on empirical functions, from simple regression models to more complex models that need local calibrations. Approaches classified as mechanistic models (21%) define the N rate based on a crop and soil simulation model, *i.e.*, computer-based tools that represent mathematically the dynamics of soil-crop-atmosphere (Wallach et al., 2018). Approaches that define N rates by applying artificial intelligence, *i.e.*, algorithms and statistical models able to analyze big data to understand underlying patterns and make inferences, were classified as machine learning (3%). Figure 2 shows the inputs for each group of algorithms. Most of the empirical models make use of data coming from vegetation sensors (73% of algorithms), often associated with N reference strips (67%) that define the optimal crop vigour used as a target. Empirical models also use reference information/measurements about the crop (*e.g.*, crop species, developmental stage; 47%), weather (41%), soil (37%) and management (32%). Mechanistic models need more inputs compared to empirical models. Common inputs of simulation models generally refer to data about the crop (94%), soil (100%), weather (100%) and management (100%) that are needed to mathematically represent agro-ecosystem processes; in only a limited number of cases, mechanistic models made use of remotely sensed data about soil (3%) or vegetation (23%). Machine learning techniques were used only in five recommendation systems, where spatially-variable measurements coming from crop (60%) and soil (20%) sensors were used together with soil (80%), weather (40%), and management (40%) data by paying more attention to costs (40%)

compared to the other algorithms.

Tables 3 and 4 describe in detail the recommendation systems based on empirical and mechanistic models, respectively.

Empirical models

The majority of these algorithms (the first which appeared in the literature) are regression models (37%) using sensor measurements applied to vegetation (72%) to estimate N rate, N uptake or to estimate crop yields from which to retrieve, in turn, N rates, thanks to empirical N response functions. They have been proposed mainly in the context of cereal crops (maize and wheat) in the USA and EU and they are characterized by fragmentation of equations and inputs, a factor that contributed to the low level of implementation in operational conditions. The most used methods are from Oklahoma State University (OSU; Solie et al., 2012) and Nebraska State University (NSU; Holland and Schepers 2010). They represent together 37% of empirical models. Their high diffusion is explained by the fact that they are commercialized using the vegetation sensors GreenSeeker (Trimble Inc, California, USA) and Crop Circle (Holland Scientific Inc, Nebraska, USA) (Muñoz-Huerta et al., 2013). Both algorithms have been fully reviewed (Samborski et al., 2009; Franzen et al., 2016) therefore here only the basic principles are reported.

The OSU algorithm relies on two hypotheses: the NDVI (normalized difference vegetation index of the crop measured in-season is a predictor of the yield; the NDVI can also estimate the yield response to N. Thanks to proper calibrations, the measured NDVI is converted into the crop expected yield with no N added. Using local N-rich calibration strips (a small part of the field with no N limitation from sowing) the response of crop yield to N is estimated, so that the yield gap is calculated and the N rate defined. Initially calibrated for winter wheat in the USA (Raun et al., 2005), it has been also calibrated for maize in the USA (Teal et al., 2006), then generalized (Solie et al., 2012) and tested for several crops (Porter, 2010) and cropping systems (Virginia Corn Algorithm, Thomason et al., 2011; North Dakota State University maize algorithms, Franzen et al., 2014; Clemson University algorithm, Khalilian et al., 2017). The various calibration equations and modifications of the original algorithm are a reason for its wide diffusion.

The NSU algorithm is based on the parametrization of a quadratic or quadratic-plateau function describing the relationship between N rate and yield, estimated by the sufficiency index. This index is defined as the ratio between the vegetation index of the actual field and the vegetation index of an N-rich strip (real or virtual, Holland and Schepers, 2013). The maximum N rate is established by the producer; recommended N rates are defined depending on the sufficiency index, the parameters of the function and the estimated contribution from the soil N pool. The NSU algorithm was proposed for maize in the USA. It accounts for 10% of the empirical models reviewed here. Other plant-based algorithms have been developed, mainly for maize in the USA, by relating chlorophyll meter readings to recommended N rates (*e.g.*, Kim et al., 2006). Finally, we also recorded algorithms with no spatialized data inputs: the maximum return to N (MRTN) approach, N-mass balance (Morris et al., 2018) and Nutrient Expert (Pampolino et al., 2012). MRTN is well-known and considers costs, resulting in the optimum economic N rates; it relies on multiple years and locations of maize N rate field trials specific for the USA (Melkonian et al., 2008). The Nutrient Expert, on the other hand, is the most used approach in the Asian countries for cereals (rice, maize and wheat). Similarly to MRTN, Nutrient Expert has been developed from regional nutrient response studies (Chim et al., 2017). Requirements for macro-nutrients are estimated from the expected yield response to each nutrient, which is the difference between the attainable yield (the one achieved following the best practices) and the nutrient-limited yield (estimated from nutrient omission trials). The inputs needed are data of growing environment characteristics, soil fertility indicators, management and yields (Pampolino et al., 2012).

Mechanistic and machine learning models

Mechanistic models are used in 21% of recorded cases. The Adapt-N model is the most representative, being used in 42% of studies on maize in the USA. The model incorporates high-resolution weather data and field-specific input information on soil, crop, and management, in order to estimate, during the growing season, the recommended N rate. Adapt-N is based on the Precision Nitrogen Management model, which simulates the growth of the crop, and the LEACHN model for the simulation of soil water and N dynamics (Melkonian et al., 2007). It is a web-based application developed by Cornell University, acquired by Yara International (Yara International ASA, Oslo, Norway), recently adapted to produce N recommendations for site-specific N management. Other crop models are used for N recommendations, sometimes considering spatial variability: STICS and APSIM for maize and wheat (*e.g.*, Bourdin et al., 2017; Puntel et al., 2018, respectively) and CERES for wheat and rice (Cui et al., 2017; Zhang et al., 2018, respectively). When the crop models are spatialized to provide site-specific N recommendations, the information from vegetation is used to carry out the ??forcing of crop model (*e.g.*, Guérif et al., 2007), while the use of soil spatialized information from proximal sensing or standard analysis is considered more than in the empirical models (Figure 2). Also, costs are considered more frequently by recommendation systems based on mechanistic models compared to empirical algorithms.

Machine learning techniques are mainly used to integrate empirical models with additional information. In fact, in two of the five publications found, machine learning algorithms were used to integrate weather and soil data that were not considered in the original studies (Ransom 2018; Ransom et al., 2019). In one study, they were used to define N recommendation using spatialized vegetation monitoring integrated with soil measured characteristics (Tremblay et al., 2010) confirming the trend for deeper data integration.

What are the temporal and geographical diffusion of these methods?

Figure 3 reports the temporal evolution of the recorded studies.

Empirical models were the first type of algorithms used, with a gradual increase since 2000. The years 2005 and 2010 corresponded to the publication of the OSU algorithm (Raun et al., 2005) and the NSU algorithm (Holland and Schepers, 2010). Starting from year 2012, studies involving Nutrient

Expert (Pampolino et al., 2012) were published, contributing to the peak registered in 2017. Mechanistic methods appeared in 2006, but only after 2015 was there a marked increase, with a maximum in 2017. Machine learning reports have increased very recently, from 2017 to 2020. Very probably, this evolution is linked to the greater availability of a large data sets, essential for the algorithm training phase, along with the increase in computing capacity.

The geographical distribution of the recorded studies is shown in Figure 4.

Most of the algorithms were developed and used in the USA, where empirical approaches (Raun et al., 2005; Holland and Schepers, 2010; and their variants) were predominant compared to mechanistic models. Also, publications in the EU mostly involved the use of empirical regression models. Mechanistic solutions were different: Adapt-N (Melkonian et al., 2008) was the most used in the USA, while in the EU no specific crop model was predominant (Guérif et al., 2007; Granados et al., 2013; Bourdin et al., 2017; Ravier et al., 2018; Morari et al., 2020; Table 4). In Asian countries, empirical models represented the majority of the approaches used (82% and 80%, respectively), while the use of mechanistic models was very limited; Nutrient Expert (Pampolino et al., 2012) was the most used algorithm, while 44% of empirical approaches consisted in attempts to calibrate the algorithms developed in the USA. Finally, studies conducted in China and India had the highest number of machine learning approaches (Figure 4).

What advanced solutions can be identified in nitrogen recommendation systems?

Our presented work also aimed at identifying "advanced solutions" in defining N doses. Four types of solutions were found, namely sensor/approach fusion, algorithm add-ons, environmental benefits, and multi-objective decisions. They were intended as attempts to account for the complexity of data coming from different monitoring systems (*i.e.,* sensor/approach fusion, algorithm add-ons) and for the different impacts of N fertilization in the agro-ecosystem (*i.e.,* environmental benefits, and multi-objective decisions).

Figure 5 shows the abundance of each type of advanced solution, separately for the two datasets:

publications with (Figure 5A) and without (Figure 5B) N recommendation systems.

“Sensor/approach fusion” and “algorithm add-ons” were the most explored solutions (40-44% and 30%, respectively). In the publications proposing an N recommendation system, “sensor/approach fusion” mainly consisted in using the proposed algorithm differently for different management zones defined by soil variability (60% of the papers), while in the group of publications with estimates of N-related variables without defining N doses (See Section 2.3), it involved the use of more complex combinations such as crop models, machine learning and/or crop monitoring to give better predictions. Only the publications proposing an N recommendation system were analyzed by considering the advanced solutions by algorithm type (Figure 6).

Within publications describing empirical algorithms, “algorithm add-ons” accounted for 41% of advanced solutions. These solutions account for the variability that was not considered in the original version of the algorithm or in the reference estimation method. In most cases these solutions used weather- or soil-correcting factors to improve the prediction (*e.g.*, Bean et al., 2018). The advanced solutions involving environmental benefits (10%) and multi-objective decisions (7%) are represented by algorithms explicitly considering N losses (*e.g.*, Lindblom et al., 2017 and Gramig et al., 2017) and taking decisions considering environmental and productive outcomes, respectively. The number of these solutions increased in the most recent years. Conversely to the studies involving empirical models, environmental effects (three studies; 21%) and multi-objective decisions (three studies; 21%), (*e.g.*, Mesbah et al., 2018; Moeller et al., 2009) were more frequently addressed with mechanistic models. On the other hand, since mechanistic models already need a high number of input data, the strategy of algorithm’s “add-on” was rare (one study, 7%). Machine learning did not consider environmental outcomes, probably because of the unavailability of a sufficient amount of data for the implementation of the algorithms.

To better clarify what can be done practically to integrate data in recommendation systems, we have identified three examples at increasing levels of complexity: i) combine free remote sensing products with low-cost proximal sensors as inputs to an empirical N recommendation system (‘sensor fusion’);

ii) combine empirical N recommendation systems with machine learning techniques to add knowledge about field properties ('algorithm fusion'); iii) combine soil and crop sensing (either proximal or remote) with a crop model ('high-level data integration').

Nutini et al. (2018) provided an example of the 'sensor fusion' strategy, by mixing satellite crop monitoring with smart apps for field scouting and site-specific N recommendation. They used free Sentinel-2 satellite products to drive field data acquisitions using smartphones as sensors to estimate crop N requirements (low, medium, high). The proposed solution is cost- and time-effective, widely applicable in operational workflows, but needs calibration of regression curves specific by rice variety group (Paleari et al., 2019), and does not account for soil and weather variability.

Ransom et al. (2019) developed an example of the second approach ('algorithm fusion'). They incorporated soil and weather variables into an empirical N recommendation system *via* machine learning, obtaining better estimates of the economically optimum N rate compared to the original system, and proving that the N recommendation system takes advantage of added soil and weather variables. A limitation of this system is the high number of input data required, and the empiricism of the method that could limit its applicability.

Jin et al. (2019) worked with the third option ('high-level data integration'): they combined remote sensing, soil properties and a crop model to derive N recommendations. The system retrieved field management zones using yields estimated from satellite-derived vegetation index and weather. The crop model APSIM used inputs from the state soil national database and simulated yields and N losses at various N rates. This system offers high-level data integration and multi-objective decision making based on economic and environmental outcomes. Its main limitations are related to the difficulty of yield estimation and accurate retrieval of soil properties for sub-field scales. It was not tested on commercial fields.

The three methods have a number of features in common: i) they need calibration of increasing complexity before they can be applied in operational conditions; ii) they need to consider spatial and temporal field variability; iii) they valorize the large data sets that are being made available by monitoring campaigns.

What are the knowledge gaps that limit the adoption of these systems?

One of the main issues linked to the limited application of N recommendation systems in operational conditions is represented by the type of algorithms proposed. Empirical models are the most studied but require calibration whenever they are applied in conditions other than those used for their setup. This is a severe limitation to their adoption. Moreover, these algorithms have been developed to be used with specific optical sensors, making their extension to other sensors cost- and time-consuming. Recent efforts have been made to develop different algorithms, based on mechanistic models and machine learning (Morris et al., 2018). They need large inputs datasets because they mathematically or statistically represent the interaction among soil, plants and weather. However, the greater effort needed to collect input data should correspond to a greater applicability of these algorithms. Despite this, their use is frequently limited to research applications. The Adapt-N is the only mechanistic algorithm that has had a commercial interest. It is used for maize in the USA, where it was developed. It was not originally developed for site-specific management (Melkonian et al., 2008). Moreover, coupling spatialized data with crop models has not yet been fully addressed. The process still has issues related to the identification of the correct scale of processes, the selection and integration of spatialized variables, their use, and the ability of the algorithm to manage uncertainty at different scales. In conclusion, one severe limitation is the poor ability of the algorithms to integrate different data sources. Our analysis showed a trend of developing advanced solutions. However, more efforts could be put in place.

Current and future perspectives

With the current availability of tools, precision N management can be carried out using the empirical recommendation systems. This requires extensive field work for their calibration. For example, specific guidelines are available to calibrate the OSU system (https://nue.okstate.edu/Hand_Held/New_N_Strategy.htm). This involves the implementation of field experiments with monitored no-nitrogen and N-rich strips in different locations. For these treatments, the NDVI is measured at side-dressing, and crop yield is measured at harvest. Alternatively, if one wants to use a more mechanistic solution, current crop models can be applied by coupling them with a customized decision support system. For example, Morari et al. (2020) have developed a decision support system based on the SiriusQuality model. When this coupling has been already realized, the system can be applied in different conditions, provided that input data are available, either directly via built-in data recovery functions or provided by the user.

Future research should focus on data and algorithm fusion and on proving the economic, agronomic and environmental benefits of the proposed algorithms at farm scales. In fact, nowadays big data are produced by precision agriculture techniques and Agriculture 4.0, thanks to the use of new soil and crop monitoring techniques together with reference measurements of soil and weather properties. A better integration of several types of data, sensors and algorithms could be carried out in order to valorize field data and to help the large-scale application of algorithms. On the other hand, the level of complexity of the algorithms must meet the knowledge and practical needs of farmers. In fact, some reviewed published works, demonstrated that more attention during the research process should be paid to overcoming the problems of implementation of N recommendation systems by developing friendly interfaces (Lindblom et al., 2017). Another factor that will allow a wider adoption of N recommendation systems is their capability to calculate and report the economic, agronomic and environmental advantages of precision compared to conventional management. This will require specific research actions aimed at measuring these advantages in the field and disseminating them.

Conclusions

Many studies have been carried out in the past twenty years to develop N recommendation systems. Many of them propose empirical N recommendation algorithms that depend on specific calibration conditions; therefore, they cannot be easily extended to soils, climates and crops which differ from those where their calibration was carried out. On the other hand, mechanistic or machine learning algorithms are hardly spatialized enough to provide site-specific N recommendations. In addition, information about soil properties, crops and weather data, and environmental outcomes is not yet fully integrated, with the result that field data are not valorized by most current algorithms. Following the trend already visible in the literature, future research must overcome the specificity of current algorithms and maximize the integration among high-resolution monitoring data sets.

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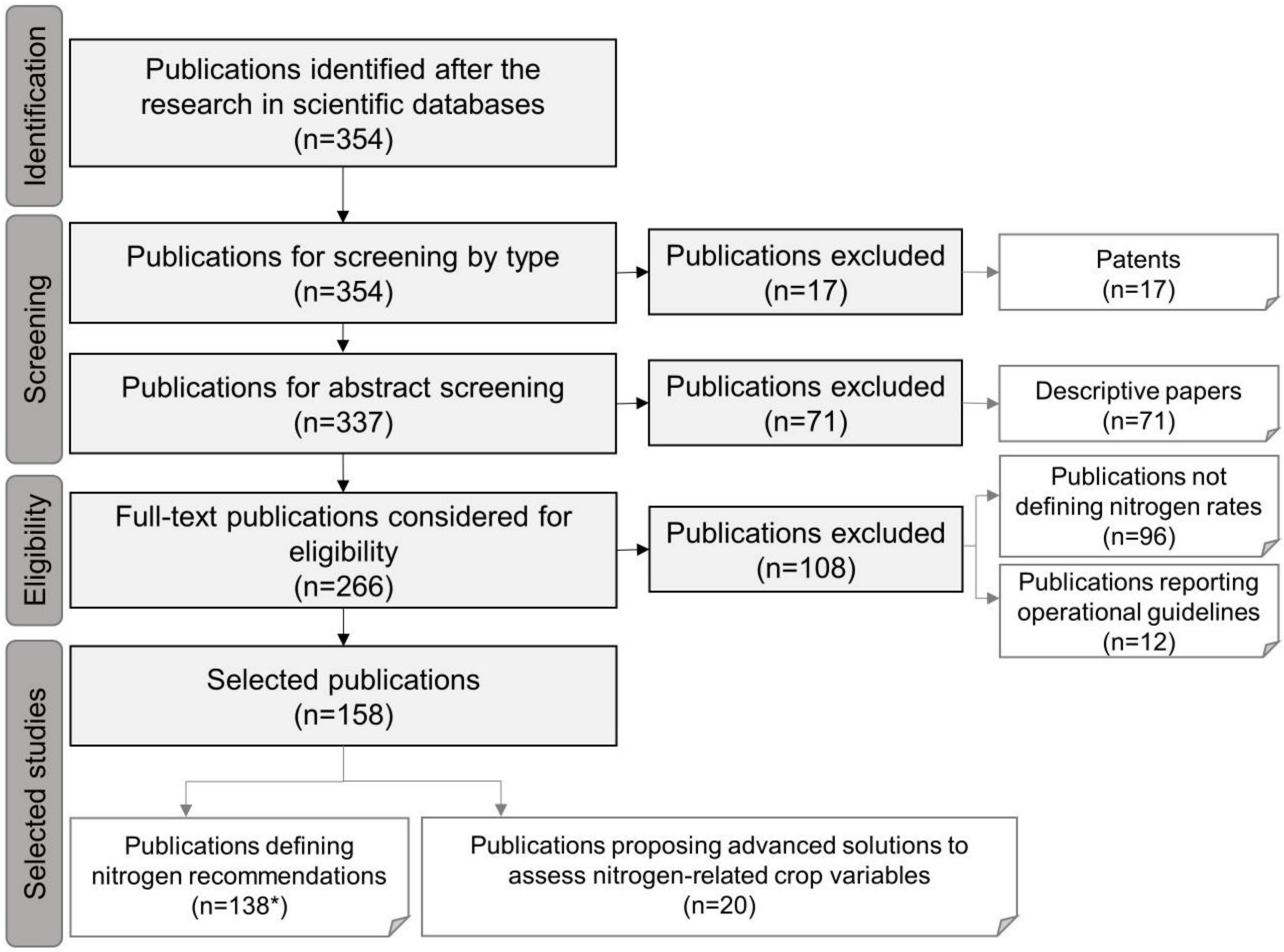

*The number of publications selected was 138, but the total number of recommendation systems is 151 because some publications reported more than one system.

Figure 1. Search flow to select the publications analyzed in this work.

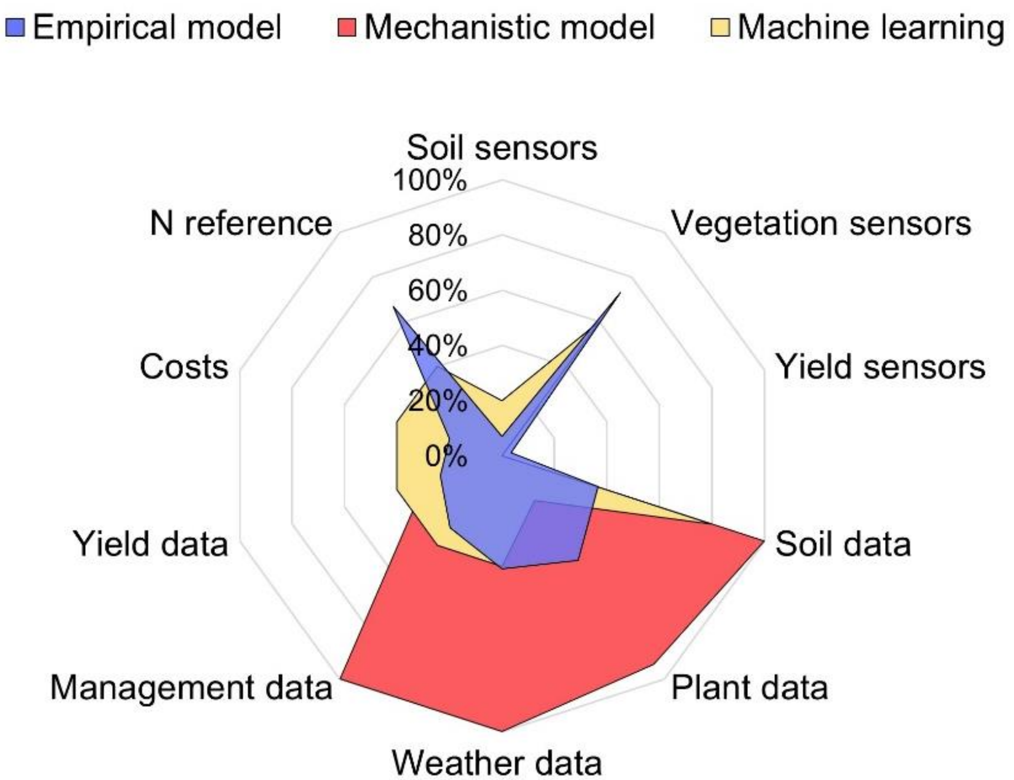

Figure 2. Spider chart showing input data to nitrogen recommendation systems based on empirical models, mechanistic crop models or machine learning techniques. The data are represented as percentage of the total records of the group.

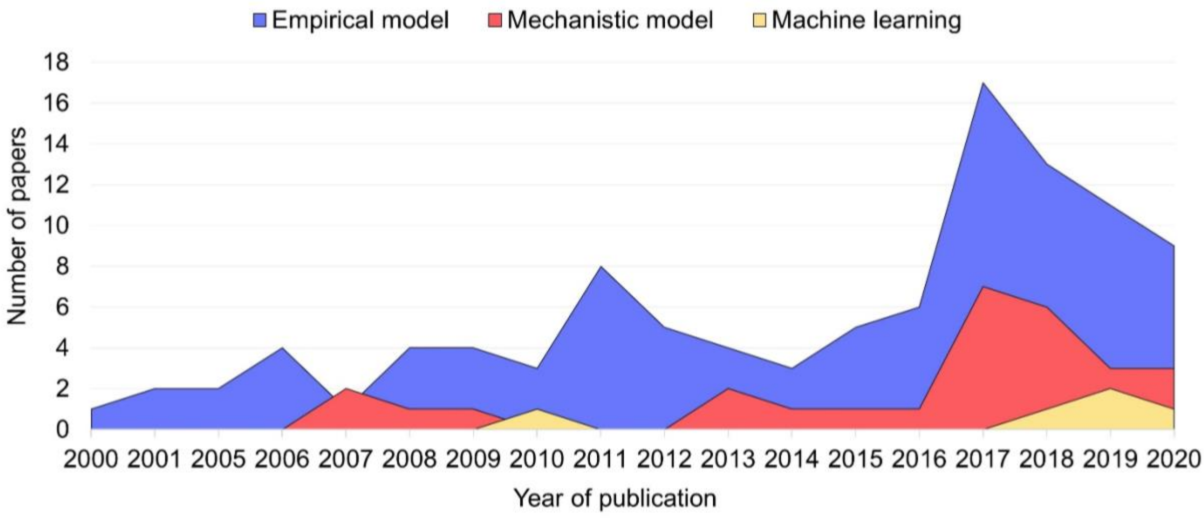

Figure 3. Number of papers describing a nitrogen recommendation system by type of algorithm and by year.

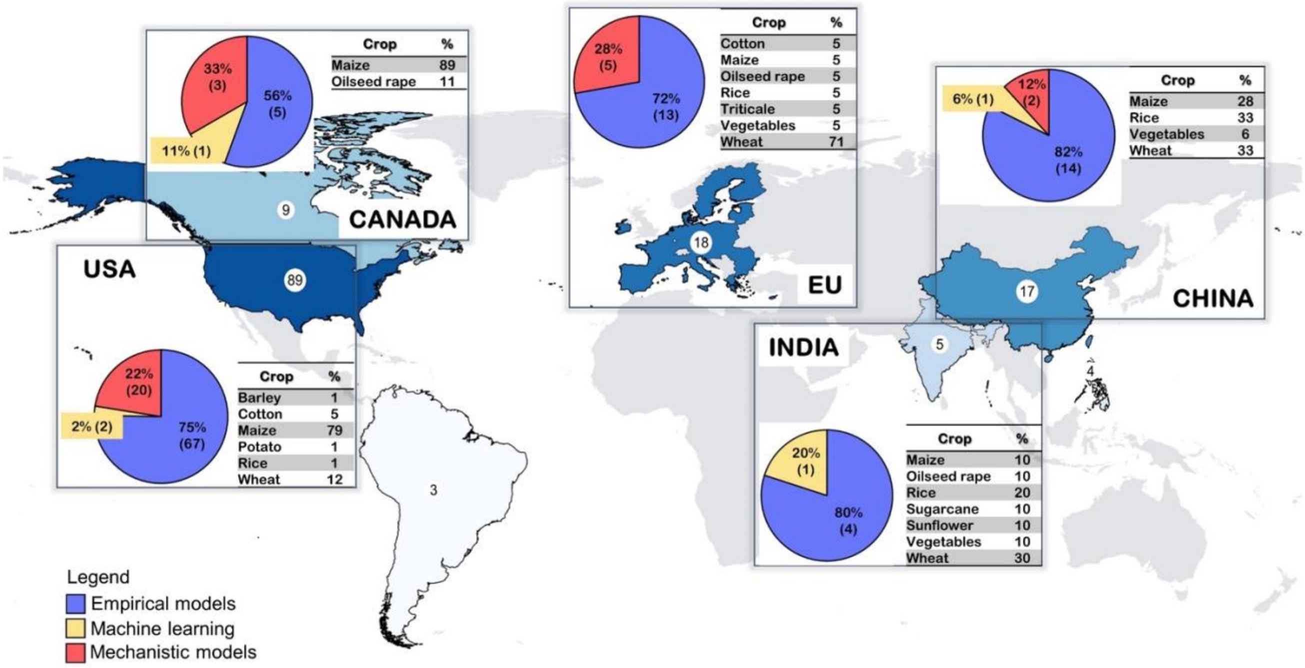

Figure 4. Map of the geographical distribution of the selected nitrogen recommendation systems. Countries with three or more studies are represented in blue (from light to deep blue) with the indication of the number of total studies. For countries with five or more studies, the statistics about the types of algorithm and the crops are presented with a pie chart and a table, respectively.

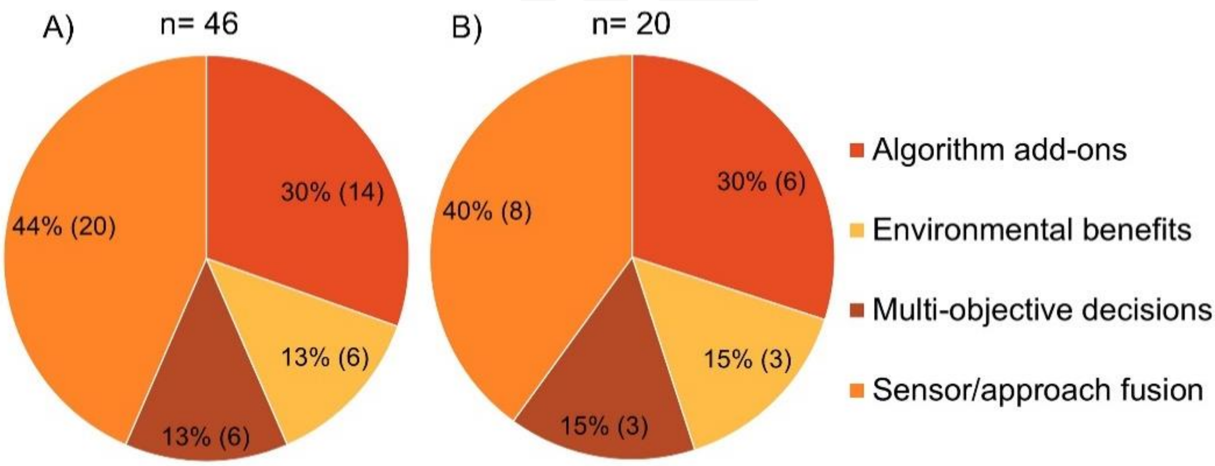

Figure 5. Percentage and number of publications (n=66) by type of advanced solution adopted. A) Publications with N recommendation systems; B) Publications without N recommendation systems.

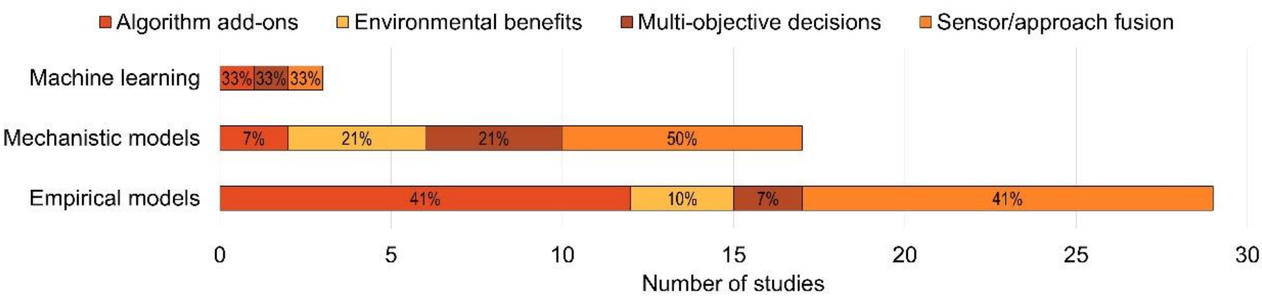

Figure 6. Frequency (%) of the adoption of advanced solutions by type of algorithm within the publications describing N recommendation systems (n=46).

Table 1. List of characteristics of nitrogen recommendation systems extracted from the selected publications.

Category	Characteristic	Possible values
Paper information	Author	
	Title	
	Year	
	Location	
Algorithm used in the nitrogen recommendation system, and its application	Algorithm	Empirical model / Mechanistic crop model / Machine learning
	Is it based on an existing system?	Yes/No
	Crop species	Name of crop species
	Timing of nitrogen application	Development stage when the recommended nitrogen rate shall be applied
	Description of method	The type of sensor, the variable that is estimated and the type of regression (for empirical methods) or the name of model/machine learning method
	Type of application	Calibration / Validation / Comparison with another N recommendation system
Spatially variable inputs	Soil sensors	Yes/No
	Vegetation sensors	Yes/No
	Yield sensors	Yes/No
Non-spatially variable inputs	Soil	Yes/No
	Vegetation	Yes/No
	Weather	Yes/No
	Management	Yes/No
	Yield	Yes/No
	Costs	Yes/No
	Nitrogen reference strips	Yes/No
Advanced solutions	Type of solution	Environmental impact estimation / Multi-objective decision / Data fusion / Add-ons
	In the case of data fusion, what was integrated?	*E.g.*, Soil and weather; Crop and weather; Soil, crop and weather, Satellite data and crop models, Machine learning and empirical model

Table 2. Breakdown of the dataset according to the algorithm implemented in the nitrogen recommendation system.

Type of algorithm	Records (n)	Records (%)
Empirical model	115	76
Mechanistic crop model	31	21
Machine learning	5	3
Total	151	100

Table 3. Details about the algorithms classified as empirical models. For each algorithm, the number and the percentage of records, inputs used, starting year, geographical distribution, and main crop are indicated. The percentage of records for each category is reported (no number means 100%).

Reviewed algorithms	Records (n)	Records (%)	Inputs from remote sensing	Measured data inputs	First year	Country *	Crop*
Regression models	43	37%	Soil (9%), Vegetation (72%), Yield (2%)	Soil (23%), Plant (26%), Weather (9%), Yield (40%), Management (26%), Costs (33%)	2000	USA (56%), EU (21%)	Maize (58%), Wheat (26%)
Oklahoma State University algorithm and modified versions	31	27%	Soil (9%), Vegetation	Soil (15%), Plant, Weather, Yield, N reference strips	2006	USA (65%), China (13%), India (13%)	Maize (42%), Wheat (39%)
Nebraska State University algorithm	12	10%	Soil (8%), Vegetation, Yield (8%)	Soil, Plant, Management, N reference strips, Costs (8%)	2010	USA (75%), EU (25%)	Maize (75%)
Nutrient Expert	12	10%	-	Soil, Plant, Weather (33%), Management, Costs (42%)	2006	China (67%), Indonesia and Philippines (17%)	Maize (42%), Rice (39%)
Chlorophyll meter algorithms	5	4%	Vegetation	Plant, Management (33%)	2006	USA	Maize (58%)
Virginia Corn Algorithm	3	3%	Vegetation	Weather, N reference strips	2011	USA	Maize (63%)
Clemson University algorithm	3	3%	Soil, Vegetation	Plant, Weather, N reference strips	2011	USA	Cotton (63%), Maize (37%)
MRTN	3	3%	-	Soil, Plant, Yield, Costs	2014	USA	Maize
N-mass balance	3	3%	-	Soil, Plant, Weather, Management, Costs (33%)	2018	Brazil (33%), Canada (33%), Turkey (33%)	Maize (63%)

* Countries and crops with more than 10% of studies.

Table 4. Details about the algorithms classified as mechanistic models. For each algorithm, the number and the percentage of records, inputs used and starting year, geographical distribution and main crop are indicated. The percentage of records for each category is reported (no number means 100%).

Reviewed algorithms	Records (n)	Records (%)	Inputs from remote sensing	Measured data inputs	First year	Country *	Crop*
Adapt-N	13	42%	-	Soil, Plant, Weather, Management, Costs (23%)	2007	USA	Maize
APSIM	5	16%	Soil (20%), Vegetation (40%)	Soil, Plant, Weather, Management, Costs (40%)	2009	USA (80%), Australia (20%)	Maize (80%) Wheat (20%)
STICS	4	13%	Vegetation (50%)	Soil, Plant, Weather, Management, Costs (25%)	2007	Canada (50%), EU (50%)	Maize (50%) Wheat (50%)
CERES	2	6%	Vegetation (50%)	Soil, Plant, Weather, Management, Costs (50%)	2017	China	Rice (50%) Wheat (50%)
Others	7	23%	Soil (14%), Vegetation (29%)	Soil, Plant, Weather, Management, Costs (14%)	2013	USA (43%), EU (43%)	Maize (57%) Wheat (29%)

* Countries and crops with more than 10% of studies