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APPLICATION OF ARTIFICIAL INTELLIGENCE FOR IRRIGATION MANAGEMENT: A SYSTEMATIC REVIEW

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KEYWORDS

artificial intelligence, machine learning, fuzzy logic, artificial neural networks, irrigation management, sensors.

ABSTRACT

A literature review on artificial intelligence in irrigation management was performed, using the Systematic Literature Review (SLR) method with explicit search criteria. More than 45,000 complete titles in 130 reference bases were consulted at once. A total of 38 primary studies were selected, which formed the basis of this review. The findings showed increasing use of Artificial Neural Networks (ANN) fed with climate and soil sensor data for irrigation management solutions. ANNs have been the most popular choice for solutions that require machine learning techniques. Fuzzy-logic-based technologies stood out in Decision Support Systems (SSD). Hybrid neuro-fuzzy approaches manage the best aspects contained in each of the two techniques (ANN and fuzzy logic). Moreover, autonomous wireless and networked sensors have been the most often used. Good chances of developing solutions for irrigation management point to the growing application of ANN-based machine learning, Support Vector Machine (SVM), and Random Forests techniques, using wireless sensor networks and computer vision with remote sensing images.

INTRODUCTION

Irrigation methods and their management are critical, especially in agricultural lands of arid and semi-arid regions in the world. Smart irrigation strategies that apply water at the right time and amount have been critical for good plant growth and hence crop productivity (Gu et al., 2017). Such a demand is most important in a scenario where there is a growing need for production under competitive cost conditions while maintaining good product quality (Pimentel et al., 2010).

Accurate quantification of water consumption by crops requires improvement of existing methods. Accordingly, the use of meteorological and soil data for decision-making in irrigated agriculture has been a fully settled reality. That said, intelligent methods to estimate plant water stress and automatically activate irrigation systems are important for saving water and energy in the management of crops.

Many techniques currently used to determine plant and soil water status require a large amount of laboratory work because they are not automated, generating high costs both because of the time and qualified professionals needed, as well as the availability of facilities in the vicinity of crops (Almeida et al., 2008).

With all these challenges and needs in mind, results of current studies have shown that the use of artificial intelligence tools is a viable alternative to increase crop production and efficiency in the use of natural resources, among which water is one of the most relevant (Udutalapally et al., 2020).

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Artificial intelligence

The term "artificial intelligence (AI)" is widely used and was first introduced by McCarthy in 1956 at a conference at Dartmouth College (Fazel Zarandi et al., 2020). According to Luger (2013), AI can be defined as "the branch of computer science that is concerned with the automation of intelligent behavior". It is beyond our scope to comment on definitions of the term "intelligent behavior"; however, most definitions of AI include the idea of solving problems using machines and programs that simulate human cognitive processes (Norvig & Russell, 2013).

Fuzzy logic

Fuzzy systems are expert knowledge-based systems that work in a rule-based fashion. Their main principle is duality, which establishes that two opposite events coexist (that is, an element can belong, to a certain degree, to one set and, to another degree, to another set). Beyond the binary systems commonly used in discrete mathematics, fuzzy logic predicts degrees of truth membership (Maia, 2007). Thus, a fuzzy rule-based software system is not only a binary classification system, it can also be used when more precise adjustments are desired, allowing the system to "think" in terms of uncertainty and approximate reasoning, which is typically associated with human behavior.

Due to their static nature, fuzzy systems cannot learn or even have the flexibility to adapt to extremely dynamic contexts. As a result, hybrid systems have emerged as a topic of interest to the scientific community (Sanchez, 2009). These systems in turn are featured by using a combined approach of fuzzy systems and artificial neural networks (neuro-fuzzy), which minimizes the limitations of using only fuzzy systems.

Machine learning

The term machine learning - ML (aprendizado de máquina - AM, in Portuguese) is the study of how to build computer programs that improve their performance at some tasks through experience. It has emerged as one of the branches of AI that has currently greater use and awareness.

ML techniques can be broadly classified into two most commonly used types (Géron, 2019):

- Supervised learning: in which the training data provided to the machine learning model also contains the predicted output (labels) for the given input;
- Unsupervised learning: in which outputs (labels) are unknown and the dataset is grouped by association rules, i.e., the machine tries to learn without instruction.

Other types are still used, such as semi-supervised learning, in which only part of the labeled data is used and the learning is by strengthening, which is completely different and rarely used.

Most of the machine learning algorithms used today, especially supervised ones, are implementations of some sort of regression models, such as linear, polynomial, or logistic, among others (Géron, 2019). Still, there is a great use of neural networks in supervised learning techniques.

Neural networks

Artificial Neural Networks (ANNs) can best be described as "a set of densely interconnected processing units which handles parallel-distributed information system and has the same concept as the biological neural networks of the human brain" (Allawi et al., 2018).

Neural networks (NNs) are composed of layers, which contain nodes called neurons. Each neuron has an associated weight that determines the strength and signal of the connection. Weights are the main form of storage in NNs, with learning algorithms updating these weights. Each neuron receives inputs, calculates the activation level and, when activated, sends a signal to its output connections (Patrício & Rieder, 2018). Internal layers between input and output nodes are called hidden layers. NNs with many hidden layers are called deep learning networks.

As per Géron (2019), several factors have contributed to making ANNs one of the most used solutions in AI today, such as the great availability of data brought by automated sensors and the increase in computational power since the 1990s.

Support vector machines

A support vector machine (SVM) is a machine learning algorithm for classification and regression problems. Its main focus is on training and classifying a dataset. When applied to regression issues, adaptations are included in its optimization function, and the name SVR (Support Vector Regression) is commonly used therein. A classic SVM classifier can classify the input points into two potential classes, using a line also called a hyperplane. As it is a non-parametric method, SVM stands out for its flexibility in representing complex functions and, at the same time, being quite resistant to overfitting (Patrício & Rieder, 2018). Supervised classification algorithms like SVM tend to have more difficulty when dealing with large datasets compared to NNs, thus requiring greater computational power.

Decision trees and Random Forests

Decision trees are supervised machine learning algorithms widely used in classification and regression problems. In such a method, several decision points are created. These points are the "nodes" of the tree and, in each of them, the decision will go one way or the other. These available sides or paths are the "branches," thus forming the basic structure of a decision tree.

One of the advantages of using this approach is eliminating the need for data normalization, with little need for dataset pre-preparation. However, it is considered an unstable algorithm since small changes in input data can trigger a big change in its structure.

Random forest is also considered a supervised learning technique for classification and regression, which combines several decision trees. Briefly, this algorithm creates several decision trees and combines them to obtain more accurate and stable predictions. Therefore, it generally obtains more accurate results than those of an isolated decision tree, but it is more complex to implement.

SYSTEMATIC LITERATURE REVIEW

A systematic literature review (SLR) is a method of literature review initially widespread and mostly used in medical and health fields. It is a way of identifying, evaluating and interpreting all relevant research available on a particular issue or subject of interest. SLR makes use of several individual studies on a common theme, known as primary studies. In this way, because it encompasses several primary studies, SLR is considered a secondary study (Kitchenham, 2004).

Most scientific studies include some sort of literature review. The big problem is that, depending on how the review was conducted, it may have little scientific value. As SLR is based on a pre-defined strategy, it allows evaluating the entire review. Some researchers, when conducting conventional narrative literature reviews, use to include only opinions that support their preferred research hypotheses, ruling out studies with different paths or points of view.

REVIEW METHODOLOGY AND PROTOCOL

This research question was made bearing in mind the need to know the current state-of-art of the use of AI in irrigation management for agriculture. This scenario will allow a better direction in new research, besides establishing bases and new hypotheses of work in this field of research. Thus, the questions of this work were:

a) What is the current scenario of research on the use of artificial intelligence (and its ramifications) in irrigation management for agriculture?

b) What artificial intelligence strategies have been used to work with data obtained from sensors such as agroclimatic, soil, or even plant parameters and perform irrigation management?

We beforehand decided that the obtained data would not undergo meta-analysis, given the great heterogeneity of studies to be retrieved and for not directly contributing to answering the proposed questions.

The platform used for the search was Capes Periodicals, which belongs to the federal government of Brazil. It is a simple way to consult more than 45 thousand complete titles in 130 reference bases at once (CAPES, 2021).

The search string was set to search English-written articles, as even studies developed in Brazil are also published in this language. However, Portuguese-written papers were also included since the search may select other language papers if keywords used are in some part of the abstract, for example.

The following string was used in the advanced search form of the *Periódicos Capes* website, which is maintained by the Brazilian Ministry of Education: *("expert system" OR "artificial intelligence" OR "fuzzy logic" OR "artificial neural network" OR "machine learning") AND irrigation*.

For string setup, the techniques most commonly associated with AI use in research and practical applications were considered (Mohan & Arumugam, 1997).

The string described above was applied to search “in the subject,” to avoid false positives. In the website form, the search can also be made "in the abstract,” only in the authors, or in all items at the same time.

The search returned 8,652 items among published books, articles, images, and audiovisual media. To continue the review, we used as inclusion criteria the works with the following characteristics:

- Language: English or Portuguese;
- Only scientific articles and only those published in peer-reviewed journals;
- Articles published in the last 6 incomplete years (from 01/01/2015 to 04/30/2021);
- Topic of interest: agriculture,
- Full text available for reading.

After applying the filters above, the number of findings dropped to 181 articles, which is a relatively large amount for a literature review. Thus, still using the relevance criterion, all titles and abstracts were analyzed and read to make sure that their subjects meet the requirements specified in the research questions previously prepared. This stage was called pre-selection, in which 74 articles were kept.

These articles were then read in full to further attest to their relevance and application in solving the two proposed questions. From this procedure, 38 primary studies were selected, which will compose the review. Figure 1 summarizes the entire process of selecting the primary studies.

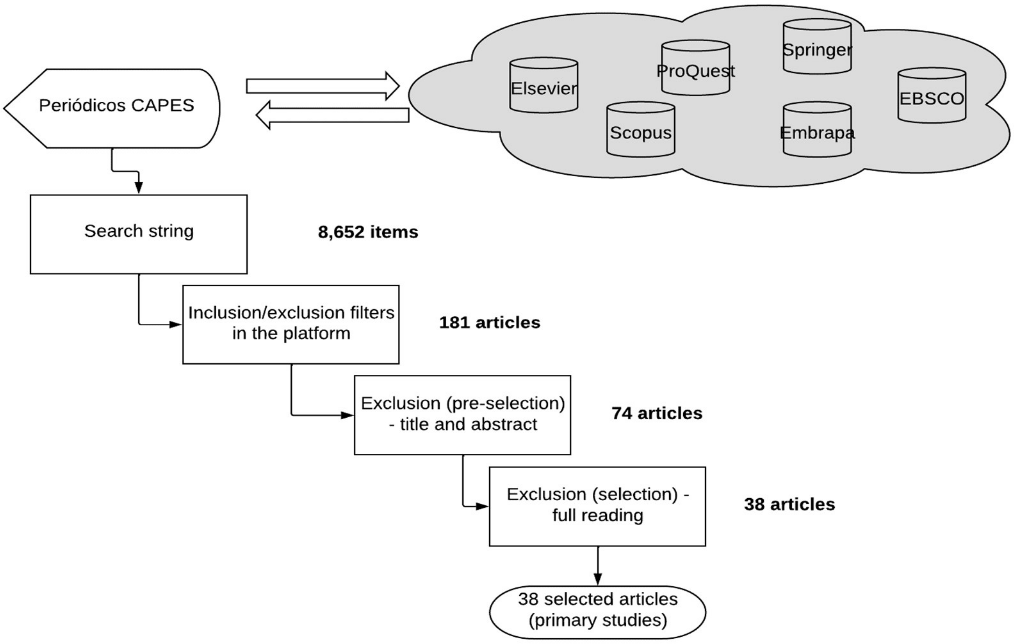

FIGURE 1. Selection diagram of primary studies. Source: the author (2021).

SLR RESULTS AND CONSIDERATIONS ABOUT PRIMARY STUDIES

To answer the guiding questions, the geographic and temporal distributions of studies were initially investigated. The results showed that the number of studies on the subject grew over the chosen period. Figure 2 shows the number of studies in the pre-selection stage for each year of the review period. We observed a clear upward trend, with a peak in 2020. It must be highlighted that studies from the current year (2021) were disregarded in this graph. Thus, as some researchers may have used data from previous years, the publication date of studies was considered.

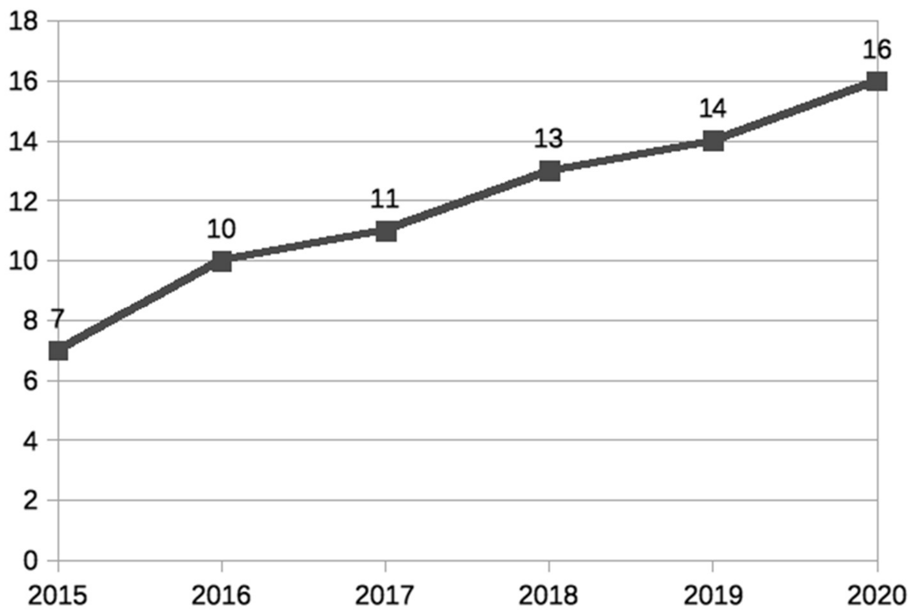

FIGURE 2. Frequency of publication of studies from the pre-selection stage. Source: the author (2021).

Geographically, the largest number of studies are concentrated in three countries: Iran, China, and the USA. These are also among the top 5 with the largest irrigation-equipped area worldwide (FAO, 2017). Iran's leadership may be due to the need for better water management due to its low availability, as most of the country's territory is under arid and semi-arid climates. Continuing in the ranking, the same logic prevails, with two great world powers (the USA and China) competing in the number of studies. These countries invest the most in research and development, in absolute numbers, according to the World Economic Forum (WEF, 2018), directly raising their positions in this research field (Figure 3).

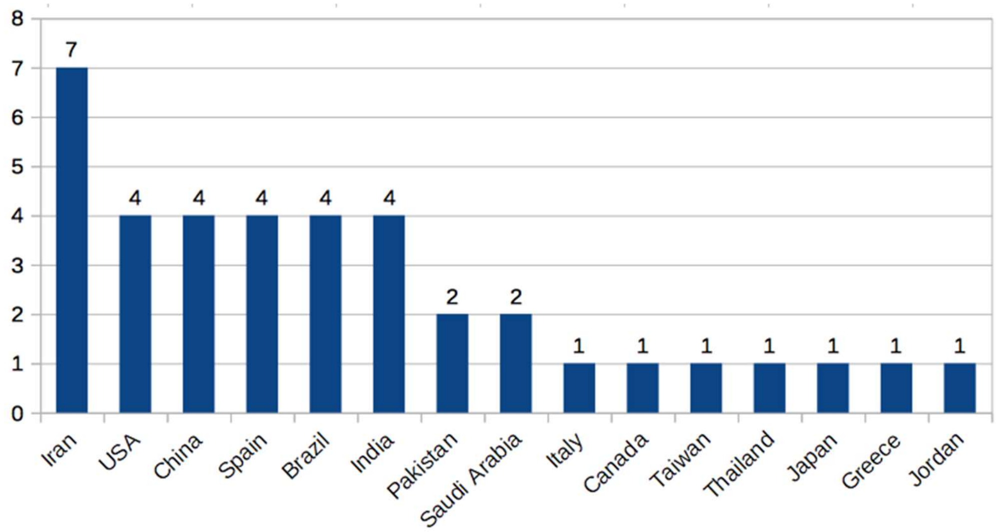

FIGURE 3. Distribution of primary studies per country of origin. Source: the author (2021).

However, it should be noted that 86.84% of the selected primary studies were developed in areas traditionally associated with a moderate risk of high water scarcity (Figure 4) (WRI, 2014).

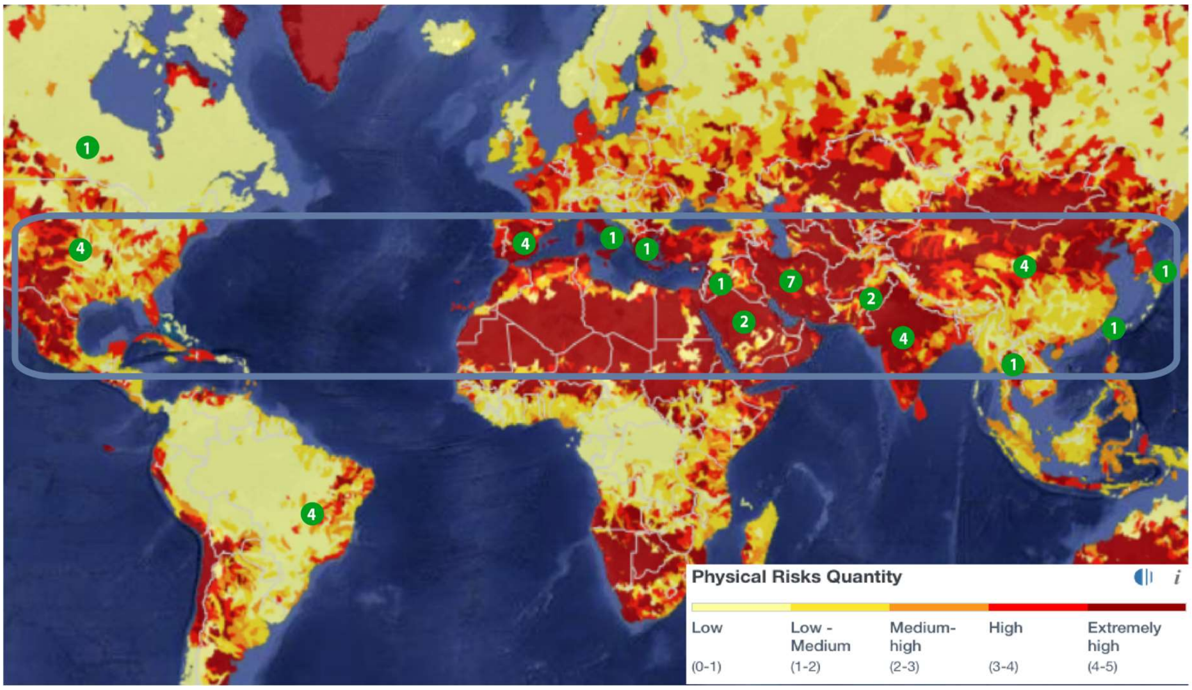

FIGURE 4. Geographic distribution of primary studies. Source: WRI (2014), adapted by the author.

For more detailed analysis, studies were grouped by the main AI technologies used. A few of them were cited in more than one category for using different techniques concurrently. Annex I shows a complete list of the selected primary studies, while Annex II provides a matrix crossing the strategies and data types used.

Neural networks use

After classifying studies by AI used, we noted that some techniques predominated. Figure 5 highlights a large use of ANNs in 17 primary studies, which were the most often used as machine learning solutions. This finding corroborates that of Géron (2019). Therefore, this tool has great growth potential to be applied to this purpose.

In a few cases, ANNs proved to be less efficient than other approaches. In comparative studies such as that of Haghverdi et al. (2015), ANN-based approaches proved to be inferior to regression algorithms, such as geographically weighted regression (GWR), to predict water content available in the soil near the root system. Seyedzadeh et al. (2020) observed an SVM variation model was superior to NNs in estimating drip-irrigation discharge rates.

NNs were used to estimate evapotranspiration in some of the selected primary studies. Feng et al. (2016) trained three neural networks (extreme learning machine [ELM], genetic algorithm optimized neural network [GANN], and wavelet neural network [WNN]) using data from 13 weather stations to estimate evapotranspiration. In this study, the first two types (ELM and GANN) obtained higher evapotranspiration estimates than already sedimented models such as Penman-Monteith (Awal et al., 2020), Hargreaves (Hargreaves & Samani, 1985), and

Priestley-Taylor (Priestley & Taylor, 1972). Kelley & Pardyjak (2019) trained a simpler NN (one 10-neuron hidden layer and one-neuron output layer) using low-cost sensor data (temperature, solar radiation, wind speed, and air humidity) collected during two weeks, which was enough to obtain solid evapotranspiration data using the Penman-Monteith method as a control. However, Raza et al. (2020) trained three NNs (multilayer perceptron [MLP], general regression neural network [GRNN], and cascade correlation neural network [CCNN]) and observed that they were not able to outperform an SVM-based strategy for evapotranspiration prediction using climatic data.

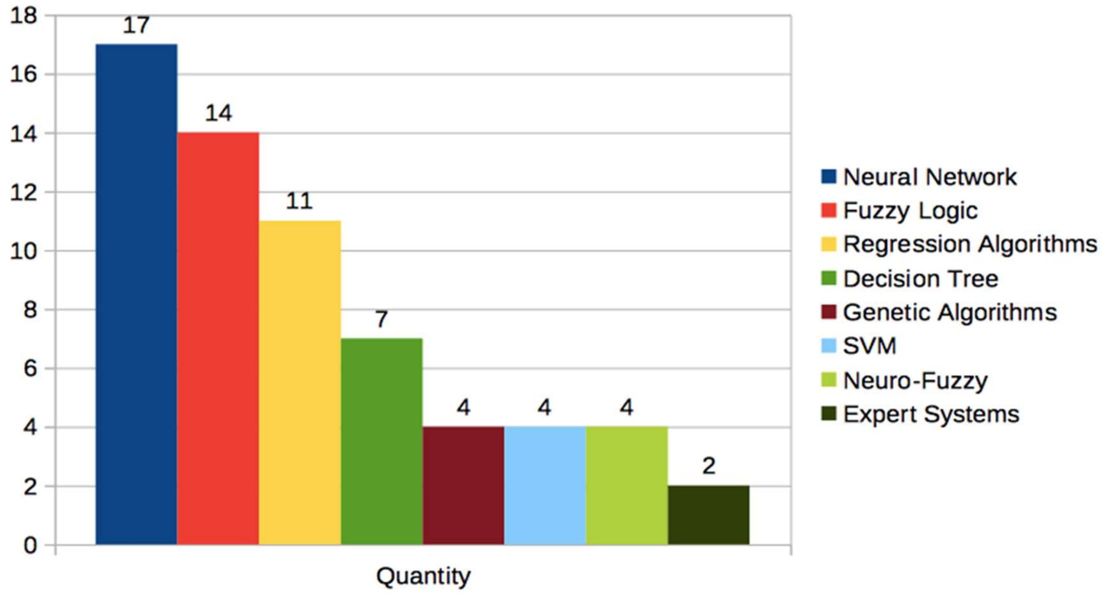

FIGURE 5. Technical approaches used by primary studies. Source: the author (2021).

In most cases, ANNs obtained better results than several regression algorithms. According to Al-Ghobari et al. (2018), ANNs outperformed multiple linear regression (MLR) to predict evaporation losses in sprinkler irrigation. Moreover, in the study by King & Shellie (2016), ANNs also outperformed MLR to predict leaf temperature in vines when using crop water stress index (CWSI).

Gu et al. (2021) used NNs for irrigation management using soil moisture data and obtained estimates 20% more accurate than water balance- and evapotranspiration-based methods, but inferior to the RZWQM2-WS method for water stress detection. In the study of Elnesr & Alazba (2017), ANN performed well in predicting wet-bulb areas in underground drip irrigation, using variables such as infiltration time, emitter discharge, and saturated hydraulic conductivity.

Innovative approaches to irrigation flow prediction were applied by Mouatadid et al. (2019), who used a long short-term memory (LSTM) recurrent neural network architecture, which was superior to a traditional ANN and MLR. The research by Nadafzadeh & Mehdizadeh (2019) tested computer vision strategies to feed a neural network and determine the wilting point of grasses and pastures and hence a proper irrigation regime, even under water shortage.

Deep learning with LSTM networks was used for irrigation management in rice by Sidhu et al. (2020a), and the results were consistent with the recommendations of a human expert and a proprietary software package. Another research to present the use of deep learning was that of Wakamori et al. (2020), who used an LSTM-based multimodal NN with changes in the grouping of environmental variables. These authors named it as C-Drop, which had a 21% precision gain in water stress estimates, using climate data and leaf images.

It should be noted that the number of strategies was greater than the number of selected primary studies (Figure 5) since some studies use more than one AI technique to achieve their objectives.

Neural networks have as strong a point a massive adoption in the most diverse contexts, having mostly positive results when compared to other strategies. The wide range of literature available, together with the increasing processing power of newer computers, designs a broadly favorable scenario for their adoption.

Fuzzy logic use

Fuzzy logic-based technologies were the second most used and found in 14 primary studies. Such a tool has been used for decades and shown great acceptance because it is based on easy-to-explain logical rules and has a history of use in commercial products (Shi et al., 2019).

Considering only studies on conventional fuzzy logic-based strategies, we observed that they are most commonly used to build SSD software. These, in turn, are widely used in simplified irrigation management, as in Yang et al. (2017). These authors obtained good results in wheat, corn, and cotton crops using data from weather stations and technical reports for the knowledge base feeding. Giusti & Marsili-Libelli (2015) also demonstrated the superiority of a fuzzy technology-based SSD versus a commercial product for irrigation management.

Villarrubia et al. (2017) used a fuzzy logic-based SSD powered by a wireless sensor network to monitor temperature, solar radiation, soil pH and moisture, air humidity, and wind speed to take decisions on irrigation. Jamroen et al. (2020) adopted a similar architecture, using a commercially available low-cost wireless sensor network to propose a fuzzy solution based on canopy temperature, solar radiation, vapor pressure deficit, and soil moisture (from a capacitive sensor). These authors could reduce water and power consumption by 59.61% and 67.35%, respectively; they also could increase crop yield by 22.58% compared to previously-scheduled drip irrigation. Likewise, Munir et al., (2018) proposed using low-cost wired sensor networks to save energy, collecting soil and air moisture data for the knowledge base feeding. These authors achieved superior results to a manual irrigation approach.

Shi et al. (2019) developed research where the decision-making system is fed multispectral remote sensing images. This advanced technique uses the images to obtain vegetative indexes associated with evapotranspiration models for decision-making on irrigation regimes via fuzzy logic. This technique was successful in mapping work shifts in center pivot irrigation at a variable rate. Another study using images to feed fuzzy decision systems was conducted by Chang & Lin (2018); they developed a small robotic tractor for irrigation and weeding in small crops. According to the authors, this automated machine is a successful idea and can be expanded to other tasks such as sowing and fertilizer or herbicide application.

Fuzzy logic also had good results in evaluating land suitability for drip irrigation compared to traditional parametric approaches (without AI), as seen in Hoseini (2019). But, as it is a non-machine learning approach, its isolated use could be replaced with other AI strategies in the coming years.

Regression algorithms

Several regression algorithms were identified in 11 of the selected studies, many with performance benchmarks. Haghverdi et al. (2015) used some geostatistical regression tools such as kriging, co-kriging, regression kriging, and geographically weighted regression (GWR), in addition to a neural network. GWR and regression kriging proved to be more efficient to predict the water availability near the roots in the soil.

Ferreira et al. (2019) compared a multivariate regression algorithm with some traditional methods (without AI) to estimate evapotranspiration, the former had better performance, especially when climatic data are limited.

Torres-Sanchez et al. (2020) tested three regression models (linear, random forests-based, and support vector [SVR]) using soil and climatic data, and all of them performed equivalent to the recommendations of an agronomist for one year of irrigation management.

In Sidhu et al. (2020b), seven machine learning strategies (6 regressions and 1 neural network) were compared to estimate water demand as a function of climatic parameters in rice irrigation management. The authors observed that the Adaboost machine learning algorithm had the best performance, with an average accuracy of 71% compared to the other models. This algorithm is characterized by iteratively adjusting regression weights.

On the Other hand, Filgueiras et al. (2020) tested six regression algorithms to predict evapotranspiration and soil water content from remote sensing images. Among them, Random Forest had the best performance for soil water prediction and the Cubist algorithm for evapotranspiration. Cubist is an algorithm where iterative decision trees are created in sequence. This model implements regression trees using instance-based and model-based learning for training data multivariate regression.

By testing eight regression algorithms for evapotranspiration prediction using remote sensing images, Dias et al. (2021) concluded for the best performance of the algorithm Cubist; therefore, it is a good alternative where there are no reliable climatic data, with a coefficient of determination (R^2) of 0.91 and normalized root mean square error (nRMSE) of 8.54%. In the work by King & Shellie (2016), MLR performed worse than a neural network to calculate CWSI in grapes using leaf temperature data. In Karandish & Šimůnek (2016), MLR could not outperform a neuro-fuzzy approach (ANFIS) to predict soil water content, using soil and climate data. The study by Navarro-Hellín et al. (2016) demonstrated a lower performance of partial least square regression (PLSR) for irrigation management compared to a neuro-fuzzy system, especially under water scarcity. In this study, climatic data obtained from weather stations, such as rainfall, wind speed, temperature, relative humidity, global radiation, and vapor pressure deficit were used. Soil data such as temperature, matrix potential, and volumetric water content were also used.

According to Al-Ghobari et al. (2018), ANNs outperformed MLR to predict evaporation losses in sprinkler irrigation. MLR also failed to outperform neural networks in predicting irrigation flow in the research carried out by Mouatadid et al. (2019), having worse performance than all other tested models.

Due to the wide diversity of regression algorithms used and their variations, we could not point out a trend or predominance of any of them, except for MLR for comparison purposes with other AI approaches, but without overcoming them in most cases.

Decision trees and random forests

Among the studies involving decision trees and random forests that are non-hybrid (which will be addressed in the later section), one can highlight the research by Torres-Sanchez et al. (2020), already mentioned above. In this study, the use of random forest-based regression, together with two other techniques (linear regression and SVR), had a valid performance for irrigation management. Moreover, Sidhu et al. (2020b), compared both decision trees and random forests with other regression algorithms. After Adaboost, both were the two that had the best performance, showing feasibility for irrigation management in rice crops.

To manage surface and underground drip irrigation, Shiri et al. (2020) used gene expression programming (GEP) and random forest with soil data to predict the wetting front dimension. Both strategies proved to be adequate, also revealing that pulsed irrigation was more efficient than continuous irrigation.

The study of Filgueiras et al. (2020), already mentioned in the section about regressions, used the random forest to predict soil water using crop coefficient (K_c), reference evapotranspiration (ET_o), solar radiation (R_o), normalized difference vegetation index (NDVI), and simple ratio index (SR) as independent variables. Random forest performed better to determine soil water and current evapotranspiration (ETa) when compared to other models such as the Cubist.

When using decision trees as classifiers, Blasi et al. (2021) showed their feasibility (97.86% accuracy) for predicting positive and negative irrigation events (to irrigate or not to irrigate), using data from soil sensors (temperature and humidity).

Using various combinations of random forests to fill in missing or missing meteorological data to estimate baseline evapotranspiration, Karimi et al. (2020) observed that 7 out of 8 random forest algorithms could fill in missing data; however, they did not perform better than the classic simple linear regression strategies.

Random forest is a quite specific model and can be used for both classification and regression. Its algorithm is relatively simple to use and fast to train, as it is based on decision trees with simple logic. However, it can be slow to make predictions after training, making it difficult to use for real-time decision systems.

Mixed or hybrid strategies

To circumvent fuzzy-logic learning limitations, researchers have bet on solutions with an ANN layer and a fuzzy logic layer. These strategies are called neuro-fuzzy, and numerous studies have applied them to different irrigated agriculture areas. Navarro-Hellín et al. (2016), for example, used them to build an SSD system for irrigation management with Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and observed their superior performance against statistical regression methods. Keswani et al. (2019) applied them in precision agriculture with neural networks, mapping soil moisture distribution, with a fuzzy system controlling irrigation valves based on such information. In turn, Kontogiannis et al. (2017) demonstrated better performance of their neuro-fuzzy solution, called FITRA, against a simple algorithm for triggering irrigation by reading soil moisture sensors.

Moreover, Karandish & Šimůnek (2016) created a neuro-fuzzy model for predicting soil water content with a performance superior to multiple linear regression and similar to an SVM-based solution, but it was not able to outperform the commercial product Hydrus 2D (PC-Progress, 2022) for the task.

Seyedzadeh et al. (2020) used several hybrid strategies to manage irrigation through drip line discharge rates. Among them, two approaches, neuro-fuzzy sub-clustering (NF-SC) and neuro-fuzzy c-Means clustering (NF-FCM), which used irrigation equipment parameters such as water temperature and water pressure in the system, obtained good results but were inferior to an SVM variation that was also used in the study.

In addition to neuro-fuzzy attempts, another mixed approach with fuzzy logic can be seen in the work of Omidzade et al. (2020), in which a learning algorithm called SARSA is added to a fuzzy solution to schedule water delivery in irrigation ditches shared among different farmers, with superior performance than an AC (Ant Colony) algorithm.

There are also fewer hybrid attempts combining genetic algorithms (GA) with decision trees, as in González Perea et al. (2019). These strategies were used to predict irrigation events based on weather data; they had an accuracy of 68% to 100% for positive irrigation events and 93% to 100% for negative ones. A combination of AG with ANN, as in Feng et al. (2016), was used to estimate reference evapotranspiration using temperature data and being superior to the Hargreaves model (Hargreaves & Samani, 1985). The same hybrid algorithm, when fed with solar radiation data, was also superior to the traditional models of Makkink, Priestley-Taylor, and Ritchie regarding evapotranspiration prediction.

Goap et al. (2018) proposed combining a supervised machine learning algorithm (SVM) and an unsupervised one (k-means clustering) to compose an integrated architecture, using climate and soil data to perform irrigation management, with its results of soil moisture prediction considered encouraging by the authors. Yet, in the research by Mouatadid et al. (2019), neural networks with wavelet transform were used, achieving results with greater precision than conventional neural networks for irrigation flow prediction.

Through the cases above, we assume that most of the studies on hybrid strategies rely on the use of the knowledge base and expertise of researchers with some algorithm, complemented with machine learning layers, mainly ANN. However, except for successful cases, mainly in neuro-fuzzy approaches, most of them obtain results that can be considered superior only to strategies that do not use any AI applications.

Other approaches

Among the less-used strategies is that proposed by Stone et al. (2015), in which a commercial expert system (ES), Irrigator PRO, was compared to manual irrigation management and obtained a similar performance. These authors used soil data from 35 tensiometers and proposed that it should be tested in later works, also in different and less uniform soils.

Torres et al. (2020) used an SVM quadratic machine learning model to calculate reference evapotranspiration and obtained values (RMSE 0.79) close to the Penman-Monteith reference model. It is worth noting that the model proposed by these authors used a smaller amount of input meteorological data if compared to the Penman-Monteith model. The model is part of a multilevel solution proposed by the authors, called Hydra, for the detection of irrigation events and automatic decision-making.

Some studies made use of genetic algorithms, as in Nadafzadeh & Mehdizadeh (2019), who used the technique to select the best image features that constituted the input of a neural network for grass irrigation management. A type of genetic algorithm called gene expression programming (GEP) was used in the research by Shiri et al. (2020), already mentioned above.

Among the approaches that use SVM, the works of Karandish & Šimůnek (2016), Goap et al. (2018), Torres-Sanchez et al. (2020), Seyedzadeh et al. (2020), Raza et al. (2020), and Torres et al. (2020).

Although not as popular as ANNs, SVM algorithms have some advantages over them, such as not getting trapped in "local minima," which stagnates the ANN learning process. However, compared to ANN, SVM takes longer to be trained, especially if a suitable kernel is not chosen.

Sensors and parameters used

Wireless sensors have been effective in providing real-time data in the use of AI strategies among the primary studies selected. Several of these studies make use of sensors to feed their algorithms and decision systems. Villarrubia et al. (2017) used temperature, soil moisture, and solar radiation sensors in a wireless sensor network. Likewise, Jamroen et al. (2020) used a wireless sensor network to collect data on soil moisture, air temperature, air humidity, canopy temperature, and solar radiation. These parameters were used to continuously feed a fuzzy system in Goap et al. (2018), who used wireless sensors (ultraviolet light, soil temperature, soil moisture, air temperature, and air humidity) to gather data for a regression algorithm. The study of Kelley & Pardyjak (2019) used low-cost sensors for temperature, solar radiation, air humidity, and wind speed to load a neural network and, in turn, estimate current evapotranspiration (ETa). Torres et al. (2020) implemented a modified wireless sensor network to reduce power consumption and equip its Hydra solution with moisture and temperature data from both soil and air. The aforementioned author also used gauge station data to compose their final results.

Wireless sensors were also mentioned in the studies by Giusti & Marsili-Libelli (2015), Navarro-Hellín et al. (2016), Kontogiannis et al. (2017), Chang & Lin (2018), Keswani et al. (2019), and Jamroen et al. (2020).

The technologies used in wireless communication were as diverse as possible, predominating the use of 3G/GPRS, Wi-Fi, and LoRa connections. As implementation depends on the location for installation of sensors and availability of communication services, future works should further evaluate the adoption of these communication protocols.

Munir et al. (2018) performed a critical analysis on wireless sensors and their high energy consumption. They proposed a solution that keeps sensors physically connected to a microcontroller, which communicates wirelessly with an access point responsible to store data in a cloud. This solution reduces potential connection issues in wireless sensor networks when used to load neural networks and other AI strategies with continuous data.

Climatic variables are the most used environmental data for AI strategies, followed by soil data, especially moisture and temperature. Moreover, in six studies, smart algorithms were used to treat images. These studies comprised the following: Chang & Lin (2018) who used a robot to weed and irrigate crops based on images analyzed by a conventional fuzzy system; Shi et al. (2019) who processed drone images using fuzzy logic to decide how much to irrigate; Nadafzadeh & Mehdizadeh (2019) who applied images processed in a neural network to assess soil water in lawns; Wakamori et al. (2020) who took leaf wilting images to aid in water stress detection; Filgueiras et al. (2020) and Dias et al. (2021) who obtained images from remote sensing mechanisms to predict soil water content and evapotranspiration.

Finally, some studies have used irrigation parameters such as pressure, water temperature, and discharge coefficient, among others. This type of approach is seen in the works of Elnesr & Alazba (2017), Al-Ghobari et al. (2018), and Seyedzadeh et al. (2020).

Upcoming trends

Some approaches are being used increasingly, e.g., SVM, random forest, and RNA. The former tended to increase from 2020 onwards. This is because SVM algorithms perform well in both classification and regression problems. However, they are slow to train when the dataset is very large, and suitable parameters are difficult to choose, such as an optimized kernel, as reported by Seyedzadeh et al. (2020), making its adoption difficult.

Fuzzy-based solutions tend to be increasingly less adopted. Despite its history of reliability and wide use, such a strategy lacks machine learning, making it more labor-intensive as requires manual interventions. Hybrid neuro-fuzzy solutions, in turn, could help to overcome the problem, but they have been superior only when compared to strategies without AI (Kontogiannis et al., 2017) or against decisions taken by experts (Navarro-Hellín et al., 2016). Karandish & Šimůnek (2016) used a neuro-fuzzy approach (ANFIS) that surpassed only MLR, being inferior to the commercial product compared to predicting soil water content. Neuro-fuzzy also performed worse than SVM as reported by Seyedzadeh et al. (2020). Finally, random forest-based strategies have grown a lot as a more powerful form of decision trees, both for classification and regression problems.

CONCLUSIONS

Having the entire methodological process described in detail in its respective section, our review is easily replicable, thus reinforcing its validity. When replicated, it could return slightly different selected publications. However, such discrepancies would be due to different personal judgments during the last two reading-based selection steps. Yet, overall findings are highly unlikely to change concerning the scenario of artificial intelligence use for irrigation management, recent studies, and future trends.

This review highlights the great predominance of artificial intelligence (AI) strategies based on artificial neural networks (ANN) and fuzzy logic in studies on irrigation and water resources management. ANNs have been mostly used for solutions that require machine learning and have had excellent performance. These networks can often be more efficient than established regression algorithms or even other AI strategies. ANN-based strategies have also proved to be more efficient than traditional equations (Penman-Monteith, and Hargreaves-Samani) for reference evapotranspiration estimates, especially when there is little data available.

Solutions implemented with fuzzy logic have excelled in decision support systems (SSD), as they work with relatively easy rules and, above all, for being a safe bet. Such systems do not have the benefits of machine learning but achieve good efficiency in non-critical environments. However, their use will decrease in the coming years, giving way to machine learning algorithms.

Approaches based on decision trees/random forests have stood out, demonstrating a growing trend in their adoption for the next few years.

There is a clear predominance of autonomous wireless sensors, interconnected in a network, referred to in most studies as WSN (Wireless Sensor Network). Most researchers build their sensors using electronic communication components, easily available in specialized stores, or using low-cost sensors. Nonetheless, in most of the studies surveyed, collected information is stored in remote databases.

Finally, there is a good chance of developing solutions for managing the various aspects of irrigation in agriculture. This is directed to increasing the use of machine learning solutions based on ANNs, random forest, SVM, and wireless sensor networks to collect data and continuously load machine learning datasets, and store the information in a cloud. Another promising path is the use of images in computer vision strategies, especially remote sensing ones, given the availability of free information that can be used in monitoring crops.

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APPENDIX I

List of primary studies used in SLR

NUMBER	YEAR	AUTHOR(S)	COUNTRY	TITLE	JOURNAL
1	2015	(Haghverdi et al., 2015)	USA	High-resolution prediction of soil available water content within the crop root zone	Journal of Hydrology
2	2015	(Giusti and Marsili-Libelli, 2015)	Italy	A Fuzzy Decision Support System for irrigation and water conservation in agriculture	Environmental Modelling & Software
3	2015	(Stone et al., 2015)	USA	Variable-rate irrigation management using an expert system in the eastern coastal plain	Irrigation Science
4	2016	(Feng et al., 2016)	China	Comparison of ELM, GANN, WNN, and empirical models for estimating reference evapotranspiration in the humid region of Southwest China	Journal of Hydrology
5	2016	(King and Shellie, 2016)	USA	Evaluation of neural network modeling to predict non-water-stressed leaf temperature in wine grape for calculation of crop water stress index	Agricultural Water Management
6	2016	(Karandish and Šimůnek, 2016)	Iran	A comparison of numerical and machine-learning modeling of soil water content with limited input data	Journal of Hydrology
7	2016	(Navarro-Hellín et al., 2016)	Spain	A decision support system for managing irrigation in agriculture	Computers and Electronics in Agriculture
8	2017	(Villarrubia et al., 2017)	Spain	Combining Multi-Agent Systems and Wireless Sensor Networks for Monitoring Crop Irrigation	Sensors
9	2017	(Elnesr and Alazba, 2017)	Saudi Arabia	Simulation of water distribution under surface dripper using artificial neural networks	Computers and Electronics in Agriculture
10	2017	(Kontogiannis et al., 2017)	Greece	Proposed Fuzzy-NN Algorithm with LoRa Communication Protocol for Clustered Irrigation Systems	Future Internet
11	2017	(Yang et al., 2017)	China	A flexible decision support system for irrigation scheduling in an irrigation district in China	Agricultural Water Management
12	2018	(Chang and Lin, 2018)	Taiwan	Smart Agricultural Machine with a Computer Vision-Based Weeding and Variable-Rate Irrigation Scheme	Robotics
13	2018	(Al-Ghobari et al., 2018)	Saudi Arabia	Prediction of wind drift and evaporation losses from sprinkler irrigation using neural network and multiple regression techniques	Agricultural Water Management
14	2018	(Goap et al., 2018)	India	An IoT-based smart irrigation management system using Machine learning and open-source technologies	Computers and Electronics in Agriculture
15	2018	(Munir et al., 2018)	Pakistan	Design and Implementation of an IoT System for Smart Energy Consumption and Smart Irrigation in Tunnel Farming	Energies
16	2019	(Shi et al., 2019)	China	Decision Support System for Variable Rate Irrigation Based on UAV Multispectral Remote Sensing	Sensors
17	2019	(Mouatadid et al., 2019)	Canada	Coupling the maximum overlap discrete wavelet transform and long short-term memory networks for irrigation flow forecasting	Agricultural Water Management
18	2019	(Ferreira et al., 2019)	Brazil	Multivariate adaptive regression splines (MARS) applied to daily reference evapotranspiration modeling with limited weather data	Acta Scientiarum
19	2019	(Hoseini, 2019)	Iran	Use fuzzy interface systems to optimize land suitability evaluation for surface and trickle irrigation	Information Processing in Agriculture

20	2019	(Nadafzadeh and Mehdizadeh, 2019)	Iran	Design and fabrication of an intelligent control system for determination of watering time for turfgrass plant using a computer vision system and artificial neural network	Precision Agriculture
21	2019	(Keswani et al., 2019)	India	Adapting weather conditions based IoT enabled smart irrigation techniques in precision agriculture mechanisms	Neural Computing and Applications
22	2019	(Kelley and Pardyjak, 2019)	USA	Using Neural Networks to Estimate Site-Specific Crop Evapotranspiration with Low-Cost Sensors	Agronomy
23	2019	(González Perea et al., 2019)	Spain	Prediction of irrigation event occurrence at farm level using optimal decision trees	Computers and Electronics in Agriculture
24	2020	(Torres-Sanchez et al., 2020)	Spain	A decision support system for irrigation management: Analysis and implementation of different learning techniques	Water
25	2020	(Jamroen et al., 2020)	Thailand	An intelligent irrigation scheduling system using a low-cost wireless sensor network toward sustainable and precision agriculture	IEEE Access
26	2020	(Seyedzadeh et al., 2020)	Iran	Artificial intelligence approach to estimate discharge of drip tape irrigation based on temperature and pressure	Agricultural Water Management
27	2020	(Raza et al., 2020)	Pakistan	Comparative Assessment of Reference Evapotranspiration Estimation Using Conventional Method and Machine Learning Algorithms in Four Climatic Regions	Pure and Applied Geophysics
28	2020	(Omidzade et al., 2020)	Iran	Comparing Fuzzy SARSA Learning and Ant Colony Optimization Algorithms in Water Delivery Scheduling under Water Shortage Conditions	Journal of Irrigation and Drainage Engineering
29	2020	(Sidhu et al., 2020a)	India	Long short-term memory neural network-based multi-level model for smart irrigation	Modern Physics Letters B
30	2020	(Sidhu et al., 2020b)	India	Machine learning-based crop water demand forecasting using minimum climatological data	Multimedia Tools and Applications
31	2020	(Torres et al., 2020)	Brazil	Multilevel data fusion for the internet of things in smart agriculture	Computers and Electronics in Agriculture
32	2020	(Wakamori et al., 2020)	Japan	Multimodal neural network with clustering-based drop for estimating plant water stress	Computers and Electronics in Agriculture
33	2020	(Shiri et al., 2020)	Iran	Simulating wetting front dimensions of drip irrigation systems: Multi-criteria assessment of soft computing models	Journal of Hydrology
34	2020	(Filgueiras et al., 2020)	Brazil	Soil water content and actual evapotranspiration predictions using regression algorithms and remote sensing data	Agricultural Water Management
35	2020	(Karimi et al., 2020)	Iran	Supplanting missing climatic inputs in classical and random forest models for estimating reference evapotranspiration in humid coastal areas of Iran	Computers and Electronics in Agriculture
36	2021	(Blasi et al., 2021)	Jordan	Machine Learning Approach for an Automatic Irrigation System in Southern Jordan Valley	Engineering, Technology & Applied Science Research
37	2021	(Gu et al., 2021)	China	Neural network soil moisture model for irrigation scheduling	Computers and Electronics in Agriculture
38	2021	(Dias et al., 2021)	Brazil	Reference evapotranspiration of Brazil modeled with machine learning techniques and remote sensing	PLOS One

Source: the author (2021)

APPENDIX II

Matrix of primary studies crossing strategies with data type used

		STRATEGIES USED								
		NEURAL NETWORK	**FUZZY LOGIC**	**SPECIALIST SYSTEMS**	**REGRESSION ALGORITHMS**	**GENETIC ALGORITHMS**	**SVM**	**HYBRID NEURO-FUZZY**	**DECISION TREES and RANDOM FORESTS**	**OTHERS**
DATA TYPE USED	**SOIL**	1-6-7-9-10-21-29-37	2-6-7-8-10-15-19-21-25	3-29	1-6-7-24-30	33	6-14-24-31	6-7-10	33-36	14
	CLIMATE	4-5-6-7-10-13-17-21-22-27-29-32	2-6-7-8-10-11-15-16-21-25	29	5-6-7-13-17-18-24-30-38	4-23	6-14-24-27-31	6-7-10	23-35	14
	IMAGE	20-32	12-16		34-38	20				
	OTHERS	26	26-28				26	26		

Source: the author (2021)