

**ARTIFICIAL INTELLIGENCE IN IRRIGATION AND DRAINAGE RESEARCH****CÉSAR DE OLIVEIRA FERREIRA SILVA<sup>1</sup>**<sup>1</sup> *Stormgeo, Avenida Mutinga, 4935, CEP 05110-903, São Paulo, SP, Brasil, cesaroliveira.f.silva@gmail.com.***1 RESUMO**

Essa nota científica apresenta a conceituação dos diferentes subcampos da Inteligência Artificial (IA), incluindo Ciência de Dados, Aprendizado de Máquina, Aprendizado Estatístico, Aprendizado Profundo e Aprendizado Generativo, para identificar e descrever as aplicações potenciais de cada um desses subcampos da IA no campo da irrigação e drenagem agrícola. A nota traz conceitos e termos elementares da IA aplicada a problemas reais na pesquisa em irrigação e drenagem, reflexões sobre os elementos das diferentes modelagens e suas aplicações, e perspectivas sobre os usos presentes e futuros destas técnicas.

**Keywords:** hidrologia, meteorologia, agricultura, ensino, pesquisa

**SILVA, COF****ARTIFICIAL INTELLIGENCE IN IRRIGATION AND DRAINAGE RESEARCH****2 ABSTRACT**

This scientific note presents the conceptualization of different subfields of Artificial Intelligence (AI), including Data Science, Machine Learning, Statistical Learning, Deep Learning and Generative Learning, to identify and describe the potential applications of each of these AI subfields in the agricultural irrigation and drainage research. The note includes concepts and basic terms of AI applied to real problems in irrigation and drainage research, reflections on the elements of the different models and their applications, and perspectives on the present and future uses of these techniques.

**Keywords:** hydrology, meteorology, agriculture, teaching, research.

**3 INTRODUCTION**

Climate variability and water resource scarcity require the implementation of advanced monitoring and control techniques, such as those enabled by the integration of remote sensors and predictive modeling technologies (Singh, Deshwal, Kumar, 2021), as well as the development of studies involving projections of increased

demand and the impacts of climate change on water availability. Another challenge is the integration of new artificial intelligence (AI) technologies into existing irrigation and drainage systems, which often lack the flexibility to integrate new technologies (Khadra; Lamaddalena, 2024). There is a growing need for interdisciplinary approaches that combine knowledge from agricultural engineering, environmental

sciences, and data science to address these challenges in a holistic manner.

In this context, it is crucial to conceptualize AI precisely and subdivide it into specific subfields to present its applications in irrigation and drainage more adequately, as AI is an extremely broad field that encompasses a vast array of techniques and methodologies. Each subfield, such as data science, machine learning, statistical learning, deep learning, and generative learning, offers distinct tools and approaches that can be applied in specific ways to solve particular problems in the agricultural context. For example, while Data Science can be used to integrate and analyze large volumes of environmental data, Machine Learning can automate and optimize irrigation systems in real time. Deep learning can be used to analyze satellite images and field sensors, whereas generative learning can simulate complex scenarios to plan future strategies. This subdivision allows for a more targeted and effective application of AI, ensuring that the solutions developed are both technically appropriate and economically viable, meeting the specific needs of the agricultural sector in tropical regions such as Brazil.

The overall objective of this scientific note is to conceptualize the different subfields of AI, including data science, machine learning, statistical learning, deep learning and generative learning, to identify and describe the potential applications of each of these subfields of AI in the fields of agricultural irrigation and drainage.

## 4 BIBLIOGRAPHICAL REVIEW

### 4.1 Fields of artificial intelligence

Artificial intelligence is an umbrella term that encompasses all attempts to create systems that can perform tasks that, when performed by humans, are considered

intelligent (Mitchell, 2019). This includes machine learning and its subfields (such as deep learning and generative learning) and other approaches, such as rule-based systems, logic, and symbolic methods (Nilsson, 2009).

Data science is a discipline that involves the use of statistical techniques, machine learning algorithms, and *big data analysis* to extract information from data (Provost; Fawcett, 2013). Data science combines elements of statistics and computing and applies mathematics to analyze large volumes of data and solve complex problems (Schutt; O'neil, 2013; Wickham; Golemund, 2016).

Machine learning *is* a subarea of artificial intelligence that primarily involves the creation of prediction or decision-making algorithms (Murphy, 2012; Hastie; Tibshirani; Friedman, 2009) through the use of statistical methods and computing techniques to identify patterns in data (Bishop, 2006).

Statistical learning is a field closely related to machine learning but with a stronger focus on statistical techniques and models to infer relationships between variables and make predictions (Hastie; Tibshirani; Wainwright, 2015).

Machine learning encompasses a wide range of algorithms that can be difficult to interpret and are called “black box” models because their construction cannot be clearly interpreted. In contrast, statistical learning tends to emphasize models that are interpretable and based on statistical theory (Cox; Hinkley, 1974).

Deep learning *is* a subfield of machine learning that uses artificial neural networks with multiple layers (deep neural networks) to model complex patterns in large volumes of data (Goodfellow; Bengio; Courville, 2016). These networks are particularly effective in tasks such as image recognition, natural language processing, and games (Le Cun, 2015; Schmidhuber, 2015).

On the other hand, generative learning is an area of machine learning that focuses on creating models capable of generating new data similar to the training data (Goodfellow; Bengio; Courville, 2014). Generative models, such as generative adversarial networks (GANs) and autoregressive models, can be used to create images, texts, music, etc., etc., from learned patterns (Radford, 2015; Kingma; Welling, 2013).

## 4.2 Applications using data science

Data science techniques enable the analysis of large volumes of environmental, climate and soil data, which are used as input data in modeling crop water requirements and optimizing irrigation systems (Sarala, 2020). For example, recent studies have used machine learning algorithms to predict crop evapotranspiration on the basis of historical weather data, which is crucial for determining the optimal amount of water to apply at different growth stages (Umutoni; Samadi, 2024).

Another relevant application is the use of data mining techniques to identify hidden patterns in large datasets from soil moisture sensors and weather stations. These techniques allow the development of smart irrigation systems capable of automatically adjusting the volumes of water applied, taking into account the spatial and temporal variability of soil and climate conditions (Rabhi *et al.*, 2021). In addition, the integration of satellite and drone data with data science models has been used to monitor irrigation efficiency and identify areas with potential for improvement, which is especially relevant for the management of large agricultural properties (Hemming *et al.*, 2020).

Data science-based predictive modeling has also been applied to drainage management in agricultural systems. Recent studies have shown that combining precipitation, soil moisture, and

groundwater flow data with machine learning models can accurately predict soil saturation events, allowing drainage systems to be operated more efficiently (Opper, Schumann, 2020; Gimpel *et al.*, 2021; Sayari; Mahdavi-Meymand; Zounemat-Kermani, 2021). This approach not only improves drainage efficiency but also helps mitigate the effects of soil erosion and nutrient runoff, which are critical problems in many agricultural regions.

## 4.3 Applications using machine and statistical learning

Machine learning has revolutionized the way in which automated irrigation systems operate. Machine learning algorithms allow systems to automatically adjust irrigation levels on the basis of real-time data such as soil moisture and weather forecasts (Murphy, 2012; Bishop, 2006). Machine learning algorithms, such as artificial neural networks and support vector machines, have been applied to predict crop irrigation needs on the basis of variables such as soil moisture, temperature, and precipitation, resulting in more efficient and adaptive irrigation systems (Singh *et al.*, 2024). These approaches enable the creation of robust predictive models that can adjust irrigation practices in real time, reduce water waste and improve agricultural productivity (Abioye *et al.*, 2022).

Data analysis from soil sensors and environmental monitoring systems allows early detection of problems related to drainage and soil health (Jayaraman, Nagarajan, Partheeban, 2022; Singh *et al.*, 2024). For example, machine learning algorithms have been used to identify soil saturation patterns that precede the occurrence of root diseases in tropical crops, allowing early intervention and loss reduction (Bilali; Taleb; Brouziyne, 2021). Another application example is the use of machine learning to optimize the operation of subsurface drainage systems by adjusting

control parameters on the basis of weather forecasts and historical water flow data (Gao *et al.*, 2023).

With respect to statistical learning, predictive models have been developed to understand and predict the behavior of drainage systems under different climatic conditions (Hastie; Tibshirani; Wainwright, 2015; Yang, Chui, 2021; Abioye *et al.*, 2022). Statistical techniques, such as linear regression models and time series analysis (Cox; Hinkley, 1974), have been widely used to predict crop water demand under different climatic and soil conditions (Mokhtar *et al.*, 2022). These models allow farmers to better plan the allocation of water resources (Silverman, 1986), ensuring that crop needs are met without excesses that could compromise irrigation efficiency.

#### 4.4 Applications using deep learning

*Deep learning* has emerged as a powerful tool in irrigation and drainage research, enabling significant advances in the accuracy and efficiency of these systems (Schmidhuber, 2015; Bengio; Courville; Goodfellow, 2016). One of the most notable applications is the use of convolutional neural networks (CNNs) in real-time monitoring of crop conditions and soil moisture in agricultural areas through analysis of satellite and drone images (Goodfellow; Bengio; Courville, 2016; Le Cun, 2015; Palmitessa *et al.*, 2022).

This approach allows early identification of water-deficient areas, facilitating rapid and targeted interventions that optimize water use (Sayari; Mahdavi-Meymand; Zounemat-Kermani, 2021; Poe, 2023).

Recurrent neural networks (RNNs) and their variants, such as *long short-term memory* (LSTM), have been applied to predict future irrigation needs on the basis of time series of climate and soil moisture data. These networks are particularly effective in modeling complex patterns of climate

variability, which are common in tropical regions, allowing dynamic adjustments of irrigation systems to adapt to real-time environmental changes (Umutoni; Samadi, 2024).

Another promising application of deep learning in irrigation and drainage is the optimization of the operation of subsurface drainage systems via models trained to predict the behavior of water flow in the soil. These models simulate the interconnection of multiple factors, such as soil texture, topography, and climatic conditions (Yang, Chui, 2021; Singh, Deshwal, Kumar, 2021; Palmitessa *et al.*, 2022). In this context, the use of deep learning models in subsurface drainage allows precise control of the system, consequently minimizing the risks of soil saturation and erosion while maintaining optimal conditions for crop growth (Gumiere *et al.*, 2020; Yang, Chui, 2021).

Deep learning techniques have been used to develop intelligent decision support systems that integrate data from multiple sources, such as field sensors, satellite images and weather forecasts, to predict and recommend highly accurate irrigation and drainage practices, which consequently results in more efficient management of water resources and the achievement of greater productivity (Sinwar *et al.*, 2019; Bilali; Taleb; Brouziyne, 2021).

#### 4.5 Applications using generative learning

Generative learning opens new possibilities for simulating irrigation and drainage scenarios, allowing researchers and farmers to test different management strategies without the need for direct interventions in the field (Goodfellow; Bengio; Courville, 2014).

Generative models, such as generative adversarial networks (GANs), can create detailed simulations of how different irrigation practices impact crop productivity under different climatic

conditions (Radford, 2015; Kingma; Welling, 2013). These simulations are particularly useful for planning long-term strategies and for developing irrigation and drainage technologies that can adapt to climate change (Bowman *et al.*, 2016). They are also important for making predictions in regions where climate variability is high and real data are scarce, allowing for better preparation and planning of irrigation and drainage operations (Akkem; Biswas; Varanasi, 2024).

Another innovative application is the use of generative learning to optimize the design of drainage systems. By generating multiple scenarios of water flow and soil conditions, generative models can help engineers identify the most efficient configurations for drainage systems, taking into account factors such as terrain topography and soil permeability (Akkem; Biswas; Varanasi, 2024). This not only improves the efficiency of the systems but also reduces operational costs and environmental impacts.

Additionally, generative models have been used to create decision support systems that help farmers choose the best irrigation and drainage practices on the basis of simulated future scenarios. These tools provide personalized recommendations that consider the specific dynamics of each field, including climate variables, soil conditions, and crop demands. By integrating these simulations with real-time data, farmers can make more informed and adaptive decisions, resulting in more sustainable water resource management.

## 5 FINAL CONSIDERS

Artificial intelligence is a broad field of research that has spread throughout academic and popular culture and is understood as any form of interaction between a machine and a human being. In this interaction, the machine, at least

apparently, learns to respond to the human being.

As it is an extensive field of study, it is necessary to subdivide it into subfields with different concepts according to their specificities to avoid misuse in academic publications and direct the researcher to the subfield that best fits their study objective.

Data science is a subfield of AI focused on extracting knowledge from data and is being used to develop decision support systems for the integrated management of irrigation and drainage systems. It combines real-time data with predictive models to optimize the use of water resources.

Machine learning is a subfield of AI that creates models to learn patterns and make predictions, whereas statistical learning is a subfield of machine learning that relies on statistical methods to make inferences and predictions. Studies using statistical techniques, such as linear regression and time series models, have been instrumental in optimizing the design of drainage systems and predicting the impact of climate change on drainage efficiency.

Deep learning is a subfield of AI that uses multilayered neural networks to learn complex representations. It is particularly useful in processing large volumes of data from satellite images and field sensors to monitor crop health and irrigation efficiency. Deep neural networks can be trained to detect patterns in image data, such as areas with water stress or drainage problems, facilitating rapid and accurate interventions. This type of analysis is crucial for large-scale agriculture in tropical regions of Brazil, where field conditions can change rapidly.

Finally, generative learning represents a subfield of AI that focuses on creating new data from models that understand the distribution of existing data. It allows the extension of small- and medium-sized datasets to improve the

training of machine learning, statistical learning, and deep learning models.

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