Artificial Intelligence (AI) as a complementary technology for agricultural Remote Sensing (RS) in plant physiology teaching

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Recepción: 28.10.2022 | Aceptado: 31.10.2022

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Citar: Ahmad, A, Noor, SE, Cartujo Cassinello, P, & Martos Núñez, V (2022). Artificial Intelligence (AI) as a complementary technology for agricultural Remote Sensing (RS) in plant physiology teaching. *REIDOCREA, 11*(61), 695-701.
Financiación: This work was supported by the projects: "VIRTUOUS" funded from the European Union's Horizon 2020 Project H2020-MSCA-RISE-2019. Ref. 872181, "SUSTAINABLE" funded from the European Union's Horizon 2020 Project H2020-MSCA-RISE-2020. Ref. 101007702, and the "Project of Excellence" from FEDER (Fondo Europeo de Desarrollo Regional)- Junta de Andalucía 2018. Ref. P18-H0-4700.
Área o categoría del conocimiento: Fisiología Vegetal – Docencia

Abstract: Agriculture is facing several challenges such as climate change, drought, and loss of fertile land, which could compromise global food safety and security. In this scenario, integration of novel technologies into agriculture could be the possible solution to address these concerns. There are several modern technology tools that can be integrated into agriculture for this purpose. Agricultural remote sensing (RS) technology, being one of the promising tools, has long been used for agriculture, but its potential has not been explored fully. RS involves monitoring and analysis of various crop growth parameters generating huge datasets. But management and interpretation of RS generated data is a complex and costly process. Therefore, artificial intelligence (AI), another promising tool of 5th industrial era, could be used to complement agricultural RS technology to improve data processing and generating visualizing results. Machine learning, a subset of AI, methods have been efficiently employed for disease detection, yield predictions, and biomass estimations. Yet, there remains a huge possibility to develop crop growth and yield simulations, and machine training models from the freely available satellite data. Hence, indicating and instilling this knowledge into young students would result in the novel initiatives in agricultural plant physiology, since most of the parameters analyzed through RS are physiological.

Keyword: Artificial Intelligence (AI)

La Inteligencia Artificial (IA) como tecnología complementaria a la Teledetección (RS) agrícola en la enseñanza de la fisiología vegetal

Resumen: La agricultura se enfrenta a varios retos, como el cambio climático, la sequía y la pérdida de tierras fértiles, que podrían comprometer la seguridad alimentaria mundial. En este escenario, la integración de tecnologías novedosas en la agricultura podría ser la posible solución para hacer frente a estos problemas. Existen varias herramientas tecnológicas modernas que pueden integrarse en la agricultura con este fin. La tecnología de teledetección agrícola (RS), que es una de las herramientas más prometedoras, se utiliza desde hace tiempo en la agricultura, pero su potencial no se ha explorado plenamente. La teledetección implica el seguimiento y el análisis de diversos parámetros de crecimiento de los cultivos, lo que genera enormes conjuntos de datos. Pero la gestión e interpretación de los datos generados por la RS es un proceso complejo y costoso. Por lo tanto, la inteligencia artificial (IA), otra herramienta prometedora de la quinta era industrial, podría utilizarse para complementar la tecnología de RS agrícola con el fin de mejorar el procesamiento de los datos y generar resultados de visualización. Los métodos de aprendizaje automático, un subconjunto de la IA, se han empleado eficazmente para la detección de enfermedades, la predicción del rendimiento y la estimación de la biomasa. Sin embargo, sigue existiendo una enorme posibilidad de desarrollar simulaciones de crecimiento y rendimiento de los cultivos, así como modelos de entrenamiento de máquinas a partir de los datos satelitales disponibles de forma gratuita. Por lo tanto, indicar e inculcar estos conocimientos a los jóvenes estudiantes daría lugar a iniciativas novedosas en la fisiología de las plantas agrícolas, ya que la mayoría de los parámetros analizados mediante RS son fisiológicos.

Palabra clave: Inteligencia Artificial (IA)

Introduction

Today agriculture sector is at the forefront of climate change, land, and water availability, which are threatening global food safety and security (Ali Ahmad, 2022; Jung et al., 2021). In this regard, technological innovations of 5th industrial era could certainly support to address these concerns. Remote sensing (RS) is one of these promising technologies that allows us to monitor crops on a large scale in a synoptic, remote, and non-destructive manner (Martos et al., 2021). However, RS has been applied in agricultural systems for 5o years (Hatfield et al., 2020), and needs further complementation by the integration of modern technological tools to harvest all of its potential in the best possible way. Various auxiliary technologies could complement RS. Nevertheless, Artificial Intelligence (AI) is the most promising of all (Boukabara et al., 2019; Mellit & Kalogirou, 2021). It can fortify the potential of RS for agricultural applications in terms of improving crop yield, disease detection, fruit and weed detection, and biomass estimations (Bah et al., 2018; Fu et al., 2020; Selvaraj et al., 2019; Wiesner-Hanks et al., 2019). Similarly, various challenges of data processing could effectively be addressed by the implementation of AI tools. For instance, machine learning, a subdivision of AI, can estimate variables with high accuracy despite of low spatial resolution of satellite imagery (Lary et al., 2016).

The complementation of RS with AI tools is evident because of the free availability of satellite imagery data. Currently, thousands of satellites are orbiting earth and generating tons of data everyday (Huang et al., 2018). Similarly, the complexity of data management and analysis, retrieved from RS tools, is a prominent challenge as reported previously (Martos et al., 2021). Therefore, it is important to harvest the potential of this new technology (AI) to support agricultural sustainability and fight against climate change. However, these objectives cannot be achieved without instilling the importance of the matter in future scientists.

This study presents useful insights about the complementation of RS with AI tools for improving plant physiological status that in return might result in increased crop yields. Similarly, the need to incorporate this subject in plant physiology studies has been stressed. Consequently, this might lead towards novel approaches and initiatives for supporting agricultural sustainability.

Remote sensing (RS)

Remote sensing offers the advantage of contactless information collection from plants, which could be of continuous nature, without altering or damaging the plants (Hatfield et al., 2020). RS technology is comprised of sensors and platforms. Platforms could be aerial, spatial, and ground-based. Air balloons, drones, and helicopters are examples of aerial platforms, while nanosatellites, microsatellites, and satellites are examples of spatial platforms. Similarly, machinery mounted, handheld, and soil installed are examples of ground-based platforms (Sishodia et al., 2020). Sensors are used to measure and detect the object reflectance. The basic principle of RS technology is based on the reflectance properties of objects i.e., every object reflects a part of the incident light that can be measured to assess various attributes (Ahmad et al., 2022). This is illustrated in Figure 1. However, sensors could be employed into the soils or plants to acquire real time data, where light reflectance principle might not be applied.

Data collected by sensors is processed and results are produced. The processed data provides information about the nutritional status, pathogen attacks, crop health, water status, and indicates the presence of stress (Hatfield et al., 2020). This information is usually provided in the form of vegetation index (VI). Several VIs has been developed and reported for estimating crop physiological parameters. For instance, chlorophyll content and leaf nitrogen were estimated by using optimized soil adjusted vegetation index (OSAVI) (Huete et al., 2002). Similarly, implication of normalized green-red difference index (NGRDI) to estimate the nutritional status of plants (Tucker, 1979) is another example of the application of VI in plant physiology. In addition, various studies on plants nutrient deficiency, evapotranspiration, water use, leaf area index (LAI), photosynthetic pigments, and global photosynthesis have been reported with the help of RS technology (Ahmad et al., 2020; Ali Ahmad, 2022; Knipper et al., 2019; Mahajan et al., 2017; Rani et al., 2019; Santos et al., 2019).

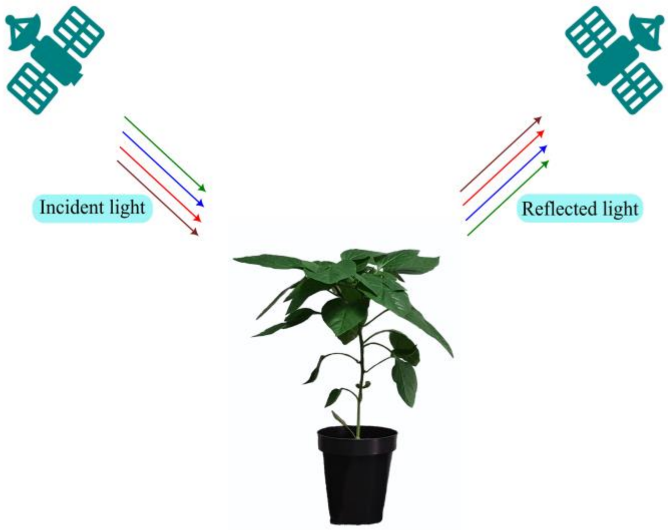

Figure 1. *Plants' light reflectance properties are used to acquire agricultural data in remote sensing (RS) technology.*

RS generates huge sets of raw data for which sophisticated processing technology is needed. The lack of efficient resources makes RS a cumbersome and costly process (Martos et al., 2021). Similarly, the resolution of images obtained through satellites is often of poor quality, which needs processing through modern technological tools to extract useful information. For instance, a spatial resolution of 1 to 3 meters is required for yield and biomass estimations (Mulla, 2013). Therefore, the complementation of RS with AI would be a promising approach to augment the efficiency of agricultural RS.

Artificial Intelligence (AI)

Artificial Intelligence (AI) is the science and engineering of employing computational intelligence to undertake various tasks effectively by making use of the mechanics of intelligence (McCarthy, 2004). AI is currently implied in almost every field of life. Broadly, AI is being used for problem solving, robotics, decision making, pattern recognition, self-organizing systems, and machine comprehension (Hunt, 2014).

Various applications of AI in agricultural domain for crop, disease, weed, pest, irrigation, and soil management have been reported (Bannerjee et al., 2018). One of the most widely used subsets, in agriculture, of AI is machine learning (ML). ML employs learning or training from mathematical and statistical methods for decision making (Ben Ayed & Hanana, 2021), which could be supervised or unsupervised. Artificial neural networks

(ANNs), a Bayesian network, a support vector machine, a genetic algorithm, a decision tree etc., could perform the function of machine. Supervised ANN is a trained model based on a specific set of inputs and outputs, and is commonly comprised of an input, an output, and one or more intermediate layers. Though, the training of ANN greatly depends on the large and highly representative data sets, meta-parameters, and choice of optimization technique. Nevertheless, a trained ANN performs rapidly and delivers optimized computations (Boukabara et al., 2019). ANN are usually employed for pattern recognition by deep learning (Gu et al., 2018). Recurrent neural network (RNN) and convolutional network (CNN) are two of the famous ANNs that can be implied for object classification, detection, and segmentation (Gao et al., 2020) on the crop data retrieved through RS. The potential of AI for data analysis and results visualization is presented in Figure 2.

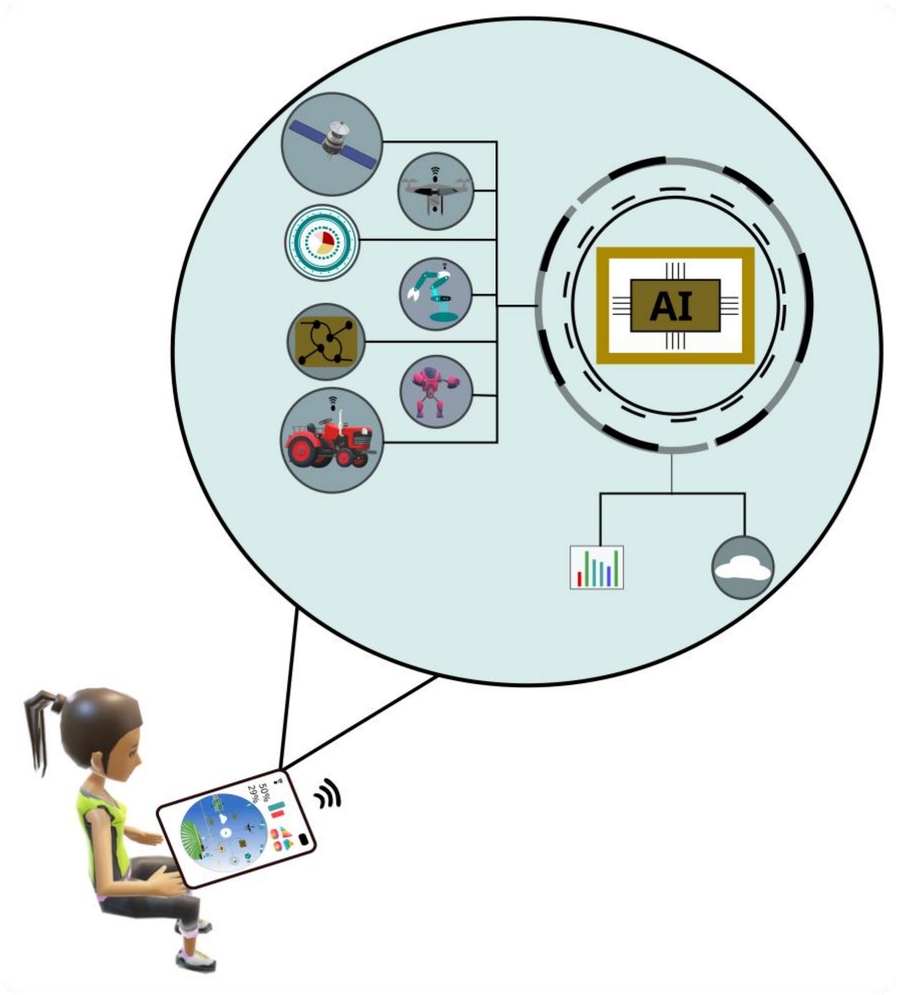

Figure 2. An illustration of the use of artificial intelligence (AI) to complement remote sensing (RS) technology for data analysis and results visualization.

ML offers the possibility of creating prescriptive and predictive models for agricultural systems. Similarly, ML have been reported to scale up the lower resolution of satellite imagery along with offsetting the complex data analysis algorithms by simple algorithms given the large and quality data for training (Jung et al., 2021). Apart from this, AI have been implied to complement RS for establishing complex empirical problems, classification problems, and model emulators development (Martos et al., 2021). However, the scope of AI to facilitate RS technology is vast. Few of the practical examples where AI complements agricultural RS are provided below.

Implications of AI in agricultural RS

Agricultural RS has several challenges for data storage, analysis, and execution of thus derived products. In this regard, AI can certainly play its role to address these challenges. For instance, stress detection is considered highly valuable in agricultural RS because it might have direct consequences on crop yield. Disease identification by detecting and classifying the lesions on a plant leaf had been achieved by employing CNN, where an overall accuracy of more than 75% was achieved (Barbedo, 2019). Similar application of deep learning for biotic and abiotic stress identification in apple, cassava, and rice have been reported (Barbedo, 2019; Liang et al., 2019; Ramcharan et al., 2017).

Application of deep learning for object detection and segmentation have also been reported for cucumber disease, rice leaf disease, sweet pepper disease, maize disease, tomato disease and pests, strawberry disease, and grapevine esca disease (Das et al., 2020; Fuentes et al., 2017; Lin et al., 2020; Ma & Chen, 2018; Nie et al., 2019; Rançon et al., 2018; Stewart et al., 2019; Zhang et al., 2019). Similarly, a model for wheat yield estimation was created using the ANN and regression models (stepwise multiple linear regression, linear regression, partial least squares regression, and multiple linear regression (Fu et al., 2020). This clearly highlights the potential of AI to analyze agricultural RS retrieved data. The already available satellite data can be used to construct yield, thermal, and vegetation index maps by using ML. This would lead to the better utilization of resources and improved decision making. In addition, generation of databases or training models for future analysis of data could be another opportunity in this domain.

Another important application of RS in agriculture requires crop and soil monitoring for decision making regarding irrigation, fertilization, and other management practices (Huang et al., 2018). This is achieved by decision support systems (DSS), which involves data acquisition, processing, and results generation to facilitate long-term or short-term decision making. However, it is very challenging to establish DSS based on the RS data. Therefore, there is need to improve the process of decision making by employing AI. For instance, knowledge based DSS make use of machine learning for reasoning. Previous data, knowledge, or decisions are employed in this scenario i.e., learning from previous solutions and experiences (Perraju, 2013). The outcome of DSS could be really promising for supporting precision agriculture and limit the unnecessary use of agricultural inputs.

However, this field requires further research. Currently, there is a lot of room to deploy DSS based on agricultural RS retrieved data. This development of DSS is limited due to various challenges including complexity of the process, poor understanding of the process by farmers, gap between knowledge based and evidence-based decision making, biological or environmental data acquisition, and high economic costs (Martos et al., 2021). Therefore, there is a need to train the future scientists and researchers to comprehend the potential and challenges of these technological tools.

Conclusion

Agriculture is facing several challenges including climate change, drought, and loss of fertile land. These are compromising global food safety and security. However, the food demand is on the rise. In this scenario, integration of novel technologies into agriculture could be the possible solution to address these concerns. RS technology has long been used for agriculture, but its potential has not been harvested to its full. RS involves monitoring and analysis of various crop growth parameters. This generates huge datasets. Management and interpretation of RS generated data is a complex and costly process. Therefore, AI could be used to complement agricultural RS technology to improve data processing and producing results in the visualization form. Machine learning methods have been efficiently employed for disease detection, yield predictions, and biomass estimations. Yet, there remains a huge possibility to develop simulation and machine training models from the freely available satellite data. Hence, indicating and instilling this knowledge into young minds would result in the novel initiatives in agricultural plant physiology, since most of the parameters analyzed through RS are physiological.

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