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Remote sensing and machine learning techniques used to predict sugarcane (*Saccharum* spp.) yield

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ABSTRACT

Objective: To gather information generated using remote sensing and machine learning models. These tools are already used in decision-making processes to support sugarcane yield prediction.

Design/Methodology/Approach: This study includes a systematic review of scientific literature. Different indicators used in studies about the prediction sugarcane yield were extracted and synthesized.

Results: This review retrieved 386 relevant studies from five electronic databases. Subsequently, using exclusion and selection criteria, 47 studies were selected for in-depth analysis. According to the analyses, the most frequently used variables were climatic variables (temperature, precipitation, and evapotranspiration) and crop variables (number of harvests). The most commonly used algorithms were random forests and multiple linear regression.

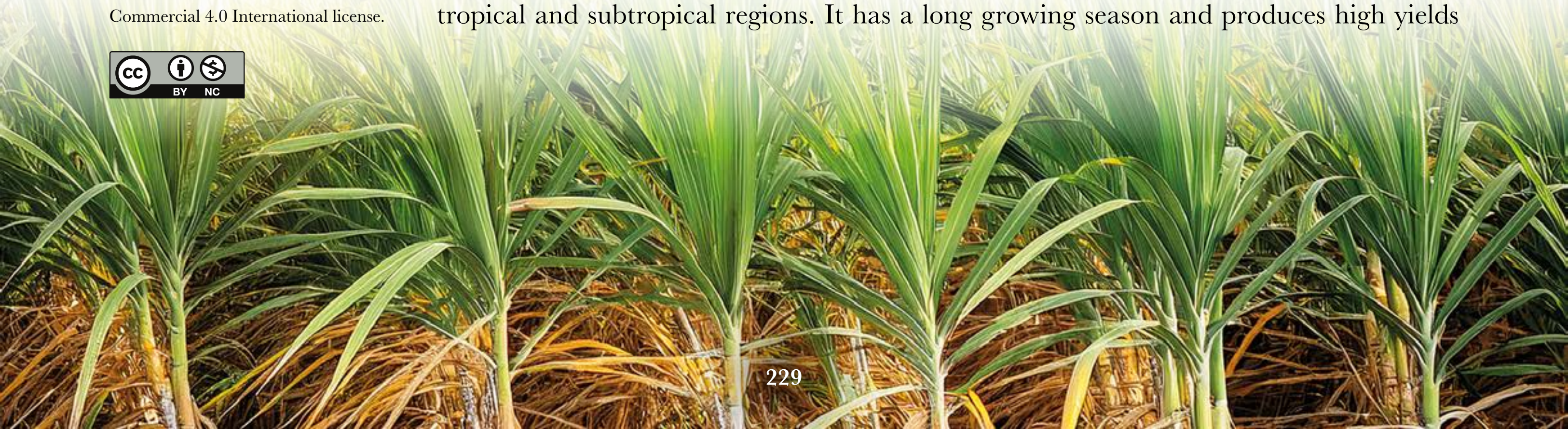
Study Limitations/Implications: The limitations are included in the in-depth analysis of the studies. These studies have great potential for further research. In this case, the analysis was limited to remote sensing and machine learning.

Findings/Conclusions: Satellites, such as Sentinel 2 and Landsat 8, are commonly used in remote sensing methods. The most frequently used vegetation indices include: Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Soil-Adjusted Vegetation Index (SAVI), and Enhanced Vegetation Index (EVI). The use of spectral bands, such as near-infrared (NIR) and shortwave infrared (SWIR), was recorded.

Keywords: remote sensing, machine learning, vegetation indices, satellite sensors, production performance prediction.

INTRODUCTION

The estimation of crop yields at different scales helps to plan food systems worldwide (FAO, 2022). Sugarcane is a species with high photosynthetic efficiency. It is grown in tropical and subtropical regions. It has a long growing season and produces high yields



and high income. The importance of this crop lies in its commercial focus, fodder production, and industrial processing. Sugarcane is used in the production of sucrose, yeast, paper, chemicals, biofertilizers, fodder, and renewable energy sources (Salgado *et al.*, 2013; Wang *et al.*, 2019; Olvera-Rincón *et al.*, 2024). Sugarcane indicators show that sucrose accounts for ∼70% of the global sugar production. In addition, it plays an important role in food and energy production worldwide (Salgado-García *et al.*, 2021; De los Santos *et al.*, 2022). The availability of information from satellite sensors and other types of advanced technology has improved the local and global prediction of sugarcane yield. Nevertheless, a closer link between remote sensing, meteorological data, agronomic parameters, and machine learning is required (Canata *et al.*, 2021). Remote sensing —as well as the use of orbital images— is applied in agriculture to identify spectral variations in soil and crop characteristics on a larger scale, supporting the diagnosis of crop agronomic parameters and improving agricultural management decision-making (Cao *et al.*, 2021; Geng *et al.*, 2021; Yzquierdo-Álvarez *et al.*, 2021; López-Castañeda *et al.*, 2022). Machine learning is applied in various fields, including agriculture, industry, commerce, and communications (Witten *et al.*, 2016; McQueen *et al.*, 1995). Crop yield prediction has always been —and will always be— a problem to be solved and a challenge to precision agriculture. So far, various models proposed for this purpose have been validated. Datasets should be included, considering the influence of physical and biotic factors, as well as crop variety on yield (Sharifi, 2021; Shahhosseini *et al.*, 2021). Machine learning detects data interactions, as well as patterns, generating new knowledge from this interaction. Since the operation of machine learning models uses datasets, the results are based on past experiences. The operated dataset includes 70-80% of the total dataset, while the rest is used for model testing and validation. Model performance statistics are determined during these stages (Tong and Nikoloski, 2021; Zheng *et al.*, 2021).

The literature review aims to clearly understand the application of remote sensing and machine learning techniques used to predict sugarcane crop yield. In addition, it helps new researchers to better understand this state-of-the-art technology (Slob *et al.*, 2021). According to Van Klompenburg *et al.* (2020), the main challenge of the application of machine learning to predict crop yield is the lack of high-quality datasets, which directly impacts the results of the models.

MATERIALS AND METHODS

The review was conducted following the guidelines of Kitchenham *et al.* (2007). Subsequently, research questions were defined. The reference databases were used to select relevant studies about the topic. The reference databases used in this study were Science Direct, Scopus, Web of Science, Springer Link, Wiley, and Google Scholar. Afterwards, the results were filtered and evaluated using a set of exclusion and quality criteria. In addition, publication sites, initial search strings, and publication selection criteria were established (Keele, 2007). Publications were selected by reviewing all databases. Subsequently, they were mainly sorted by authors, year of publication, and type of publication. Once the required information was successfully extracted, it was synthesized to provide an overview of the relevant publications published to date. Results were documented and research questions were addressed during the final stage, also known as review report (Snyder, 2019). Figure 1 shows the steps followed in the review protocol strategy.

Purpose of the research

The following six research questions (RQs) were used in this study:

RQ1. What type of problems do remote sensors and machine learning techniques solve?
RQ2. What machine learning algorithms have been used for the prediction of sugarcane yield?
RQ3. Which remote sensors are most commonly used to predict sugarcane yield?
RQ4. What dependent and independent variables have been used for sugarcane yield prediction with remote sensing and machine learning?
RQ5. What evaluation approaches/parameters have been used to predict sugarcane yield with remote sensing and machine learning models?
RQ6. What challenges have been reported using remote sensing and machine learning for the prediction of sugarcane yield?

Search strategy

The search was narrowed down to the basic concepts relevant to the scope of this review. The initial search included "aprendizaje automático (machine learning)," "teledetección remota (remote sensing)," "predicción de rendimiento (yield prediction)," and "caña de azúcar (sugarcane)." The search resulted in 386 studies. Subsequently, the results were reported and the questions answered (Van Klompenburg *et al.*, 2020). Exclusion criteria were used to guarantee the selection of relevant studies and to reduce the possibility of biased criteria (Kitchenham *et al.*, 2007). In order to include a publication, all exclusion criteria must be false. The exclusion criteria included:

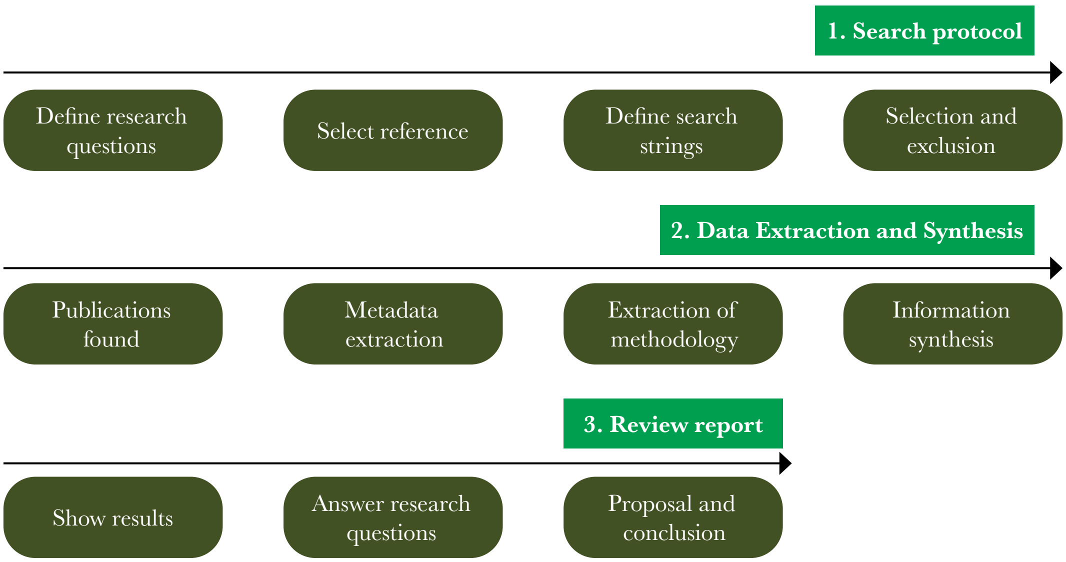


Figure 1. Details of the review protocol process.

1. The publication is not related to agriculture, yield prediction, and machine learning;
2. The publication is not written in English;
3. The publication is a duplicate or has already been retrieved from another database;
4. The full text of the publication is not available;
5. The publication is a review document;
6. The publication was published before 2010.

To answer the questions, data from the selected studies were extracted and synthesized. The retrieved information focused on verifying whether or not the studies met the requirements established in the exclusion criteria and on answering research questions.

The review was then conducted following the guidelines of Kitchenham *et al.* (2007). Using reference databases such as Science Direct, Scopus, Web of Science, Springer Link, Wiley, and Google Scholar, the results were subsequently filtered and evaluated based on a set of exclusion and quality criteria, in order to determine publication sites, initial search strings, and publication selection criteria (Keele, 2007). The publications were selected by reviewing all the duly-organized databases. Finally, research objectives were addressed in the results documentation (Snyder, 2019).

RESULTS AND DISCUSSION

A total of 386 publications were reviewed in all databases. After applying the six exclusion criteria, 47 studies were selected. Table 1 shows the number of initially retrieved publications (NIRP) and the number of publications after the exclusion and selection criteria (NPAESC). In addition, it shows that 97.9% of the publications were obtained from Google Scholar, Springer Link, and Science Direct.

Figure 2 shows the distribution of the selected publications per year of publication. An increase in the use of remote sensing and machine learning techniques to predict yield in sugarcane cultivation was recorded. The trend followed a beta distribution.

Selected publications

The exclusion and selection criteria were used to filter the initial 386 publications that were selected to answer the research questions. These criteria incorporate elements

Table 1. Distribution of publications according to the databases.

Database	NPI	NPIC	PP (%)
Google Scholar	154	32	68.1
Science Direct	70	7	14.9
Springer Link	134	7	14.9
Web of science	22	0	0
Wiley	5	1	2.1
Total	386	47	100

*NIRP (NIP)=number of initial retrieved publications; NPAESC (NPIC)=number of publications after the exclusion and selection criteria; and PP (PP)=percentage of publications according to the database.

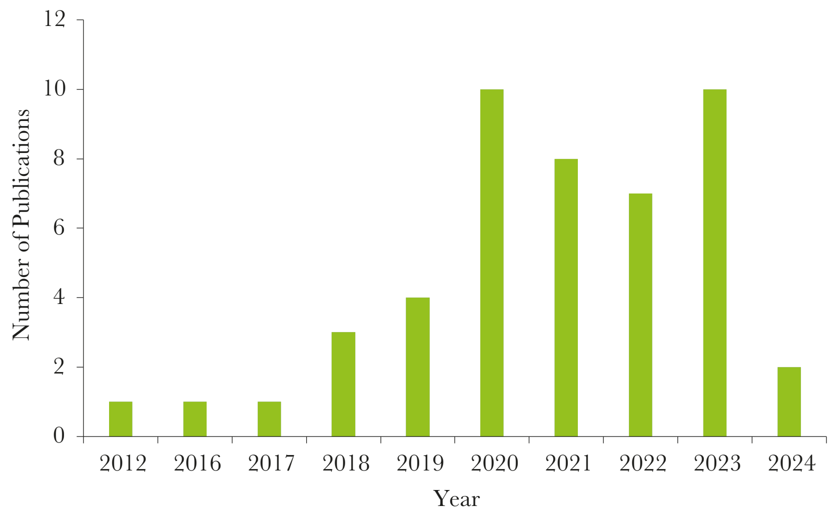


Figure 2. Distribution of publications per year of publication in the databases.

included in the thesis topic. These problems are addressed using remote sensing and machine learning techniques (Miphokasap and Wannasiri, 2018; Wang *et al*., 2019; Militante *et al*., 2019; Wang *et al*., 2020; Chea *et al*., 2020; Shendryk *et al*., 2020a). Likewise, climatic indicators, soil and crop variables, and spectral bands reported in the literature were used to predict sugarcane yield through machine learning and remote sensing techniques. The most used variables were related to climatic variables (66%). Crop yield was the dependent variable. The soil variable group included information about soil texture and moisture, slope, and the use of digital elevation models. An important finding of this sugarcane cultivation review was the use of spectral bands, such as Red, Green, Near Infrared (NIR), and Shortwave Infrared (SWIR). These spectral bands have been used as predictor variables, obtaining better adjustments than vegetation indices (Canata *et al*., 2021). Meanwhile, in the group of crop variables, the number of cuts has been considered as a predictor variable. This situation has been fundamental to explain the high importance of machine learning models in sugarcane yield prediction (Hammer *et al*., 2020; Pignède *et al*., 2021; Oré *et al*., 2022). Table 2 includes the evaluation parameters used to predict sugarcane yield with remote sensing and machine learning techniques.

Table 2. Evaluation parameters for sugarcane yield prediction using machine learning and remote sensing techniques.

Key	Statistical evaluation parameter	Times used
RMSE	Root mean square error	31
R^2	"R-squared"	34
MAE	Mean absolute error	10
MSE	Mean square error	3
MAPE	Mean absolute percentage error	6
Cor	Pearson correlation	4

Almost all studies used Root Mean Square Error Approach (RMSE) and R^2 as measures of model quality. Most machine learning models produced highly accurate results for their evaluation parameters —*i.e.*, the model made correct predictions (Canata *et al.*, 2021; Oré *et al.*, 2022). The evaluation approach was based on the K-fold method and cross-validation was the preferred choice among researchers (Chea *et al.*, 2020; Dos Santos Luciano *et al.*, 2021; Kanwal *et al.*, 2021).

Publications were reviewed to identify any issues or suggested improvements for future models in order to answer research question six (RQ6): the challenges reported in the literature for predicting sugarcane yield with remote sensing and machine learning. Several studies reported the scarce data available and the lack of real-time data to support local interventions (Canata *et al.*, 2021; Shendryk *et al.*, 2021). The studies confirmed that their prediction methods worked with the limited data available and indicated that more diverse data should be used for further testing (Xu *et al.*, 2020), including different climatic circumstances, different vegetation, and longer time series of sugarcane yield (Medar *et al.*, 2019; Rahman and Robson, 2020; Maldaner *et al.*, 2021). Adding more data sources could also improve the prediction of sugarcane yield with machine learning models (Pignède *et al.*, 2021; Galphade *et al.*, 2022).

Consequently, the authors of this research recommend the use of more machine learning algorithms, spectral bands, and vegetation indices. These indices should be calculated at different sugarcane phenological stages, in order to detect response changes in climatic variables and to correlate them with those variables, particularly in regions with clear climatic changes. Keeping an historical record of the yields obtained in sugarcane plots is fundamental to build more robust models. Due to their practicality and low cost, the use of satellite sensors is essential to capture larger areas in sugarcane mills. Therefore, the use of major and up-to-date sources, such as Sentinel 2 and Landsat 8, is fundamental. Likewise, research about the use of Unmanned Aerial Vehicles (UAVs) is essential to obtain field data that can be used to generate a larger number of observations. Currently, obtaining field data is very expensive and requires a great effort (Som-ard *et al.*, 2021). Therefore, UAVs could be integrated into the machine learning yield modeling process, because they can substitute field measurements and can cover larger areas of sugarcane plantations.

CONCLUSIONS

This systematic literature review showed that the selected publications used a range of predictor variables, depending on the scope of the research and data availability. Each publication researched sugarcane yield prediction through machine learning and remote sensing; however, they use different predictor variables. The scale of the studies is also different. The studies indicated that models with more features did not always provide the best performance and adjustment for yield prediction. The various studies used many algorithms. No specific conclusions can be drawn about the best model used for this purpose; nevertheless, the results clearly showed that some machine learning models are used more than others. The most commonly used models were random forest and multiple linear regression. The most important satellite sources were Sentinel 2 and Landsat 8. The vegetation indices most commonly used as predictors were NDVI, GNDVI, SAVI, and

EVI. Likewise, the use of indices obtained from drone-mounted RGB cameras provided promising results for the low-cost prediction of sugarcane yield. This review would guide future research about the development of the problem for the prediction of sugarcane yield, using machine learning and remote sensing techniques.

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