A Review of Remote Sensing in Sugarcane Mapping

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Abstract— **Sugarcane, a significant essential economic crop for sugar products, bioethanol, and fiber material, is cultivated around the world near tropical regions, such as Brazil, India, China, and Thailand. The sugarcane spatial distribution data efficiently supports various applications of sugarcane management. A greater number of academic articles are heading to address sugarcane mapping. Furthermore, various machine learning algorithms have been used in sugarcane mapping based on diverse Earth Observation (EO) data that achieve considerable classification performance. This paper provides a brief review of sugarcane mapping in recent years. Specifically, this paper aims to: (1) summarizing and comparing remote sensing flatform depending on the various sensors; (2) reviewing different sugarcane mapping techniques with different machine learning methods; (3) describing the essential challenges in sugarcane classification under current remote sensing techniques and trying to discover a patient method for efficient sugarcane mapping.**

Keywords—remote sensing, sugarcane mapping, machine learning, earth observation

I. INTRODUCTION

Sugarcane is an essential food and economic crop near tropical regions, spreading in many countries of the world [1]–[3], which provides around 70% of sweet sugar products for human society [4], and the bagasse serves livestock feeding, electricity generation, paper production, and ethanol creation [1], [5], [6]. As the most efficient crop to generate biofuel products such as ethanol [7], sugarcane is a crucial crop for human food security, industrial development, and sustainable energy generation. The Indian historical record from more than three thousand years ago is the earliest one to demonstrate sugarcane cultivation, and the discussion of initial sugarcane cultivation regions involves Southeast Asia, Indonesia, and New Guinea [8]. With industrialization and globalization, sugarcane is widely cultivated in South and North America, the Caribbean, Asia, Australasia, and Africa, such as Brazil, India, China, Thailand, Indonesia, Melanesia, New Guinea, U.S. [8]. Brazil is the greatest producer of sugarcane and its biofuel [6]. Since the significance of sugarcane for human society, agriculture, and industry decision-makers is necessary to gain trust, in-season, low-cost, frequently updated data on sugarcane cultivation acreage and location [9]. Satellite remote sensing has been a cost-efficiently data to satisfy the above demands depending on the multireflection information of the earth's surface that frequently covers large areas [10], [11]. Diverse remote sensing sensors provide various spatial-temporal data, such as Sentinel-1 Synthetic Aperture Radar, Sentinel-2 MultiSpectral Instrument, Light Detection and Ranging (LiDAR), and unmanned aerial vehicle (UAV), to mapping sugarcane distribution data products [12]–[16]. Meanwhile, machine learning technique hugely accelerates remote sensing data applications in crop mapping [17]–[20]. Moreover, some newly designed machine learning approaches with satellite remote sensing data are successfully used in sugarcane planting mapping [21]–[24].

In this review, we briefly review three aspects of sugarcane mapping: 1) principal sensors used for the sugarcane mapping and relevant research; 2) machine learning-based sugarcane mapping techniques; 3) challenges and future directions.

II. DATA SOURCE FOR SUGARCANE RESEARCH

Earth Observation (EO) can obtain massive large-scale earth surface data that involves many crops and sugarcane spectral, optical, and microwave information, timely and cheaply monitoring their growing situation including location, area, and healthy, and solving the information source of global sugar production [10], [25]. Relevant satellite remote sensing data as the source, since the last century, has become the principal information carrier for mapping the crop types distribution, detecting the growing situation, and assessing the damage, especially, in recent decades with the sensors and satellites increasing around the earth, huge quantities of remote sensing data powerfully supports these tasks [10], [26], [27].

From June 2015, the Sentinel-2 satellite carried a multi-spectral, high-resolution, and wide swath sensor, beginning to collect the Earth's surface images with a 5-day revisit frequency. The sensor owns 13 spectral bands with resolution from 10 m to 60m. Because of global coverage ability and the above characteristics, it has become a significant EO data source in climate change and land use land cover monitoring [14], [24], [28]. Meanwhile, Sentine-2 data is widely used in sugarcane classification and yield prediction on a large scale across different countries [22], [29]–[32]. Another European Space Agency EO mission – Sentinel-1 is a C-band synthetic aperture radar remote sensing satellite with VV and VH polarization patterns, 10 m resolution, and high revisit frequency. Since the ability to cross clouds, the objectives could include agriculture, forest, and vegetation monitoring, marine environment monitoring, sea ice observations, and so on. It is also used in sugarcane detection and yield estimate in massive cloud cover regions[16], [33]–[35]. Furthermore, the composition of Sentinel-1 and Sentinel-2 works widely in these fields as well

[23], [36]–[38]. The UAV-LiDAR data merge other optical data to serve sugarcane biomass, canopy, height, yield prediction, and growing mapping for the small-scale regions [16], [39]–[42].

III. Application of Machine Learning for Sugarcane Mapping

In decades, machine learning techniques are widely used in agriculture remote sensing classifications, boosting the improvement of crop type mapping for large-scale regions. This section reviews remote sensing sugarcane mapping articles using multiple methods to illustrate the reality of research.

A. SVM

Nihar et al. [43] combined Sentinel-1 and Sentinel-2 either to classify the sugarcane based on random forest and SVM classifiers. The 0.95 kappa coefficient of sugarcane classification was claimed from the SVM classifier. Verma et al. [44] compared unsupervised classifier-ISODATA, supervised classifier-MLC, and a kind of decision tree approaches based on vegetation indices to classify sugarcane from LISS IV imagery. As a result, the decision tree method was verified to obtain a better accuracy of 89.93% and a kappa coefficient of 0.86. Wang et al. [22] compared four machine learning methods (SVM, random forest, ANN, and CART-DT) in sugarcane classification using Sentinel-2 NDVI series for each phenology stage (seedling, elongation, harvest). The result confirms that Polynomial-SVM, RBF-SVM, RF, and CART-DT classifiers had producer's and user's accuracies greater than 91%. ANN's accuracy was lower. Mulianga et al.[45] used maximum likelihood classifier identifying sugarcane from Landsat NDVI and NDWI datasets in Kenya, separately. The classification validation illustrates that the sugarcane map achieved 83.3% overall accuracy from NDVI classification and 90% overall accuracy from NDWI. Kai et al. [46] used the k-Nearest Neighbours algorithm (kNN), Support Vector Machines (SVM), Random Forests (RF), and the Dense Neural Network to classify sugarcane from Sentinel-2 Orthorectified images. SVM had a precision of 99.55% followed by the neural network (six hidden layers) with an accuracy of 99,48% and then random forests, then finally kNN. Neto et al. [47] utilized different methods like principal component analysis (PCA), and factorial analyzing the way their stalks reflect light in the visible and near-infrared range. PCA results were invalid since two of the four sugarcane varieties overlapped. Factorial discriminant analysis, PLS-DA, and SFDA had correct classifications of 0.81, 0.82, and 0.74, respectively. Kumar et al. [48] used the M-statistic and Jeffries-Matusita (J-M) distance methods to find spectral separability among crop types. The SVMs, neural network algorithms, and maximum likelihood classification were compared to class separability and classification accuracy. Using Z-test and χ2-test, results showed that SVMs with a polynomial kernel of degree 6 outperformed other classification algorithms, providing higher accuracy for agricultural crop classification using LISS-IV data. To address the issue of sugarcane disease and optimize crop yield, Kumar et al. [49] used sensors to find optimal temperatures, humidity, and moisture situations to maintain favorable conditions for crop growth. KNN clustering and a SVM classifier identify sugarcane infections through the 200 images. The model had an overall accuracy of 96% on a test dataset. Villareal et al. [42] employed orthophotos and LiDAR datasets to map sugarcane in each growing stage based on the object-based image analysis method. The SVM among them processes the classification. Results showed the distribution of sugarcane across the establishment, tillering, yield formation, and ripening stages as 6.65%, 11.61%, 13.89%, and 17.90% respectively, with corresponding accuracies of 88%, 94.4%, 96.3%, and 91.7% for each growth stage.

B. Random Forest

Everingham et al. [50] aimed to determine the effectiveness of using the random forests algorithm and different predictor variables to predict annual variations in sugarcane crop size, thus providing valuable information for decision-making in the industry. The random forest algorithm was able to rank the importance of each predictor variable when building the decision trees. Results indicate that the random forest models had an OOB (out-of-bag) classification rate of at least 86.36%. To overcome the strains of clouds in the sugarcane planting regions, Jiang et al. [51], 2019, tested Sentinel-1 time series data to produce the initial sugarcane map using random forest and extreme gradient boosting classifiers and then removed non-vegetation class by marker-controlled watershed segmentation with Sentinel-2 NDVI series. The article claims their sugarcane map products own around 86.3% overall relative accuracy. Lozano-Garzon et al. [52] created training dataset from load data of farms and Landsat-8, Sentinel-2 data, and used multiple classification techniques (K Nearest Neighbors, Random Forest, Support Vector Machine, and Neural Networks). As a result, the random forest approach was the best, yielding 0.85 accuracy and 0.91 F1 score. Ramirez-Gi et al. [53] used random forest based on Sentinel-2 images and spatial analysis to indirectly detect sugarcane injury, providing an option to understand population change of sugarcane under specific pest damage, predicting a 17% reduction from the expected yield.

C. Neural Networks and Others

Wang et al.[36] developed a pixel- and phenology-based approach to identify sugarcane using Sentine-1, Sentinel-2, and Landsat-7/8 data to produce the sugarcane maps. The claimed overall accuracy in the 2018 map is 96%. Sreedhar et al. [38] combined with Sentinel-1 Vertical Horizontal band and Sentinel-2 NDVI time series data, employing Long Short-Term Memory neural network, identifying sugarcane in the Western Uttar-Pradesh region of India. A high accuracy of classification was claimed in this article. Lee et al. [54] used farmers' cell phone crowdsourced geolocated crop data and satellite data to build the training dataset, constructing supervised (1D CNN) and unsupervised (K-means) methods to generate high-confidence sugarcane maps with 0.67 overall accuracy. Virnodkar et al. [29] constructed a novel dataset- CaneSat as the training data, utilizing 2D CNN and four deep CNNs (AlexNet, GoogLeNet, ResNet50, and DenseNet201) to identify sugarcane. The highest accuracy achieved among these models was 88.46% within the 2D CNN, whereas four deep networks own more than 73% overall accuracy. Poortinga et al. [55] aimed to map sugarcane fields in Thailand and mitigate the occurrence of burning using a lightweight deep learning program, as an alternative to more expensive approaches like convolutional neural networks (CNN). The researchers employed MobileNetV2 and experimented with three different methods: a pre-trained approach (RGBt), randomly initialized weights (RGBr), and randomly initialized weights incorporating the NIR channel (RGBN). Among them, the pre-trained model demonstrated superior performance, achieving accuracy rates of 95.5%, 92.65%, and 90.03% respectively. Zheng et al.[56] used a mature time-weighted dynamic time warping method (TWDTW) to match the sugarcane NDVI series based on Landsat 7-8 and Sentinel 2 satellite data, producing the 2016-2019 sugarcane harvest map for Brazil. The 2018 result owns 91.47% overall accuracy. Zhou et al. [57] developed an object-oriented classification method based on the machine learning approach for sugarcane mapping using time series Huan-Jing 1 satellite images in Suixi County of China. The classification model was constructed by the AdaBoost data mining algorithm using 382 sugarcane fields from the history period. The article illustrates overall classification-93.6% and Kappa coefficient-0.85.

IV. CURRENT CHALLENGES AND FUTURE TRENDS

Satellite data with massive clouds has been a significant restrict condition to process time series sugarcane classification. Especially, most sugarcane planting regions are around tropical regions that are covered by much more clouds than other places. The combination of optical satellite data and C-band SAR data is the main solution for this issue. Sugarcane ground truth data, as the training label, is crucial to the classification quality of machine learning models and needs massive time consumption. Trusted pixels from historical official crop data can be a new option for integrating the training samples [17]–[19]. Meanwhile, sugarcane owns variable planting date that limits time series satellite image classification performance that needs a relatively stable phenology timeline. The curve matching techniques, such as the time-weighted dynamic time warping method (TWDTW) [56], provide an encouraging path to ignore growing date drift. Furthermore, this study also enlightens on a one-class classification method using phenology curve information for sugarcane that just needs one class training samples, owning possible to be the next generation sugarcane mapping technique.

V. CONCLUSIONS

This review provides a summary of the sugarcane classification based on the current remote sensing technology. Comparing literature, the Sentinel-2 optical data, Sentinel-1 C-band SAR data, and Landsat series data are the famous data source in classifications. With AI techniques development, supervised classifiers were accepted by most researchers and obtained encouraging results in sugarcane identification. Among them, SVM, random forest, and neural networks act as essential effects in these classifications and predictions. However, there are still some challenges, such as satellite image quality, variable phenology timeline, and training data extraction. This paper predicts that multisource data merging combinates with the machine learning method will be the pragmatic development in sugarcane mapping.

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