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Unveiling Agricultural Landscapes: A Methodological Review of SAR for Crop Area Estimation

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ABSTRACT

Accurate and timely information on crop areas is essential for informed decision-making in agriculture, from farm management to food security assessments. Synthetic Aperture Radar (SAR) data has emerged as a game-changer in this field due to its ability to image landscapes through cloud cover and its sensitivity to vegetation structure. This review paper delves into the various methodologies employed to utilize SAR data for effective crop area estimation. We begin by the significance of crop area information and progressively dive into the crucial image processing techniques used in SAR data analysis. These techniques encompass preprocessing steps to remove noise and artifacts, segmentation to delineate individual crop fields, and feature extraction to capture relevant crop characteristics that influence the radar backscatter. Following this, we examine the classification algorithms employed to identify and differentiate crop types within the segmented regions. We discuss both established supervised machine learning algorithms like Support Vector Machines (SVM) and Random Forest (RF) and unsupervised machine learning algorithms like K-means clustering and cutting-edge deep learning approaches like Convolutional Neural Networks (CNNs) for robust and automated crop classification. Furthermore, we explore the concept of time series analysis in the context of SAR data. By incorporating data acquired at different points throughout the growing season, these methods leverage the dynamic changes in backscatter associated with various crop growth stages. This improves differentiation between different crop types and facilitates more precise area estimation. Finally, we acknowledge the limitations and challenges associated with SAR-based crop area mapping, such as the sensitivity to soil moisture content and the potential confusion between crops with similar characteristics.

Key words: *SAR, Crop Area Mapping, Machine Learning Algorithms, Crop Classification, Remote sensing.*

Introduction

Timely and accurate monitoring of cropland extent is essential for crop yield estimation, agricultural land use administration, and climate change simulations (Waldner *et al.*, 2015). Farmers rely on this data to optimize resource allocation, manage crop health, and predict yield. For policymakers, crop area information is essential for formulating agricultural policies, monitoring food security, and managing food supply chains. International organizations use crop area data to assess global food production trends and identify potential food shortages. Traditional methods of crop area estimation, such as ground

([1]Ph.D Scholar, [2]Ex-Professor, [3]Assistant Professor, [4]Associate Professor) surveys and field reports, are often time-consuming, expensive, and limited in spatial coverage.

Unveiling Landscapes: SAR – An All-Weather Solution for Agriculture

Synthetic Aperture Radar (SAR) has emerged as a powerful tool for crop area mapping due to its unique capabilities. Unlike optical imagery, which relies on sunlight for illumination and can be hampered by cloud cover, SAR transmits microwave pulses that can penetrate clouds and fog. This allows for consistent data acquisition regardless of weather conditions (Skriver, 2012), making it particularly valuable for agricultural monitoring in regions with frequent cloud cover. Additionally, SAR data is sensitive to the structure and dielectric properties of vegetation. The backscattered radar signal (reflected signal) varies depending on the type and growth stage of crops, allowing for differentiation between different crop types. The feasibility of using crop classification with SAR data has been proven in many studies (Lee *et al*., 2001; Del *et al.*, 2003; Jia *et al*., 2011; McNairn *et al*., 2009).

The Sentinel-2 constellation was launched in June 2015 and March 2017, which shortened the revisiting cycle to 10 days for single satellites and five days for satellite constellations. The Sentinel-1A and Sentinel-1B data are freely accessible by the European Space Agency. Another example of a SAR-based satellite is RADARSAT by the Canadian Space Agency, which is not freely accessible.

Materials and Methods

SAR Data Processing for Crop Area Mapping

Preprocessing Techniques: Mitigating Noise and Artifacts

Before utilizing SAR data for crop area mapping, several preprocessing steps are essential to ensure data quality. Raw SAR data can contain noise introduced during the acquisition process or due to electronic components in the sensor. Preprocessing techniques like filtering and radiometric calibration are employed to remove noise and ensure consistent signal strength across the image.

Segmentation: Delineating Crop Fields

Once the SAR data is pre processed, the next step involves segmenting the image into individual segments corresponding to potential crop fields. Segmentation algorithms group pixels with similar characteristics into regions, effectively separating fields from surrounding features like bare soil, forests, or urban areas. Various segmentation techniques can be employed, such as thresholding based on backscatter intensity or more advanced methods like edge detection or region-growing algorithms. The choice of segmentation method depends on the specific characteristics of the SAR data and the desired level of detail for field boundaries.

Feature Extraction: Capturing Crop Signatures in SAR Data

Following segmentation, feature extraction techniques are used to identify and quantify characteristics of the SAR signal that are relevant for differentiating crop types. These features capture the "signature" of the crops within each segment. Common features include backscatter intensity, texture measures (describing spatial variations in backscatter), and polarization properties (related to the orientation of the radar wave). By extracting these features, the data becomes more suitable for subsequent classification algorithms that aim to identify the crop type present in each segmented region.

Classification Algorithms for Crop Type Identification

Machine Learning Methods

Within the realm of crop area mapping using SAR data, machine learning algorithms play a pivotal role in classifying and identifying different crop types based on the extracted features. Once relevant features are extracted from the SAR data, classification algorithms are used to identify the crop type present in each segmented field.

Crop area mapping with SAR data leverages two main paradigms of machine learning: supervised and unsupervised learning.

Supervised Learning

Supervised learning algorithms excel at classification tasks, where they learn from labeled data to predict the category (crop type) of unseen data points. Here, we explore two prominent supervised learning methods widely used in crop area mapping:

Support Vector Machines (SVM)

SVMs strive to create the optimal separation line (hyperplane) that maximizes the margin between classes. This margin refers to the distance between the hyperplane and the closest data points of each class, called support vectors. By finding this optimal hyperplane, SVMs can effectively classify new, unseen data points based on their location in the feature space relative to the hyperplane.

SVMs excel at handling situations with high dimensionality (many features) and a limited number of training samples. Additionally, they offer a high degree of interpretability, allowing us to understand which features contribute most to the classification decision. However, SVMs can be computationally expensive for very large datasets and might struggle with complex, non-linear relationships between features and crop types.

Random Forest (RF)

Breiman introduced the ensemble machine learning algorithm Random Forest (RF) for categorization (Breiman, 2001). Because of its high classification accuracy, this method is well-liked in the remote sensing field and has been effectively applied to numerous applications (Belgiu and Drãguþ, 2016), such as the detection of landslides and the mapping of agricultural and urban areas.

Random Forest (RF) builds an ensemble of decision trees, creating a "wisdom of the crowds" approach for classification. Each tree independently classifies a data point based on its internal decision rules, and the final classification is determined by a majority vote among all the trees in the forest.

This ensemble approach offers several advantages. RF is robust to outliers and noise in the data, as errors made by individual trees can be averaged out by the majority vote. Additionally, RF can handle complex non-linear relationships between features and crop types by combining the decision rules of multiple trees.

Unsupervised Learning

Unsupervised learning algorithms deal with unlabeled data, aiming to identify hidden patterns or structures within the data itself. In crop area mapping, a common unsupervised method is:

K-means Clustering

This method groups data points into a predefined number (k) of clusters based on their similarity in the feature space. K-means can be useful for the initial exploration of SAR data, potentially revealing clusters that might correspond to different crop types. However, it requires selecting the optimal number of clusters beforehand and might not be suitable for complex or overlapping data structures.

Deep Learning Techniques: Convolutional Neural Networks (CNNs)

Recent advancements in artificial intelligence have introduced deep learning algorithms, such as Convolutional Neural Networks (CNNs) which have drawn enormous attention in computer vision tasks, including image classification (Rawat and Wang, 2017; Krizhevsky *et al.*, 2017) and semantic segmentation (Long *et al.*, 2015; Ronneberger *et al.*, 2015). CNNs are a class of artificial neural networks specifically designed to learn complex patterns from image data. They can automatically extract relevant features directly from the SAR image without the need for explicit feature engineering. This allows CNNs to learn more intricate relationships between the backscatter signal and crop types, potentially leading to higher classification accuracy compared to traditional machine learning methods.

Time Series Analysis: Unveiling Crop Dynamics with Sequential SAR Images

Capturing Growth Stages for Improved Differentiation

A powerful approach for crop area mapping involves analyzing a series of SAR images acquired at different points throughout the growing season. This time series approach captures the dynamic changes in the backscatter signal associated with the various growth stages of different crops. Early in the season, backscatter might be low for all crops as they emerge from the soil. As the season progresses, crops with different growth patterns and canopy structures will exhibit distinct backscatter signatures. By analyzing the changes in backscatter over time, the differentiation between different crop types becomes more pronounced. This allows for more accurate classification and ultimately leads to a more precise estimation of crop area.

Enhanced Crop Area Estimation

By incorporating a time series analysis, the boundaries and characteristics of individual crop fields become clearer. Early season images can be used for initial segmentation, while later images with more pronounced crop-specific backscatter signatures can be used to refine the classification and ensure accurate area estimation for each crop type. This approach provides a more comprehensive picture of the agricultural landscape and allows for a more robust estimation of total crop area compared to relying on a single SAR image.

Challenges and Limitations

Sensitivity to Soil Moisture Content

One of the challenges associated with using SAR data for crop area mapping is its sensitivity to soil moisture content. Changes in soil moisture can affect the backscatter signal, potentially leading to confusion between different crop types or misclassification of bare soil as a specific crop. This challenge can be mitigated to some extent by incorporating additional information, such as historical soil moisture data or weather data, into the analysis.

Confusion between Similar Crop Types

Another limitation of SAR data is the potential for confusion between crops with very similar characteristics, particularly during early growth stages. Crops with similar canopy structures or planting times might exhibit comparable backscatter signatures, making differentiation challenging. This limitation can be addressed by combining SAR data with other remote sensing sources, such as high-resolution optical imagery, which can provide additional information on crop color, texture, or phenology (growth stages).

Conclusion

While SAR data offers a powerful tool for crop area mapping, its capabilities can be further enhanced by integrating it with other remote sensing sources. Combining SAR data with high-resolution optical imagery can leverage the strengths of both data types. SAR provides information on crop structure and growth stages, while optical imagery offers details on crop color, texture, and phenology. This fusion of data allows for a more comprehensive characterization of agricultural landscapes and leads to more accurate crop type identification and area estimation.

Advancing Classification Algorithms for Enhanced Accuracy

The field of crop area mapping using SAR data is constantly evolving, with ongoing research aimed at developing more sophisticated classification algorithms. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), hold significant promise for further improving the accuracy and efficiency of crop classification. Additionally, research on incorporating multi-temporal SAR data (multiple images acquired at different times) and integrating SAR with other remote sensing sources is ongoing. These advancements will continue to enhance the capabilities of SAR technology for providing crucial information on crop areas, ultimately contributing to improved agricultural practices, food security monitoring, and global food production assessments.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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