Cross-Region Crop Type Recognition Using Few-Shot Learning: A Systematic Review

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Abstract:- In this paper, a comprehensive survey of few-shot cross-region crop type recognition based on time-series remote sensing data is introduced. Emphasizes the integration of few-shot learning, prototype-based adaptation, and Time-Series Foundation Models for dealing with domain shift and few labeled data in agricultural applications. The survey covers the traditional machine learning, deep learning, and transformer-based approaches to crop classification using multi-temporal satellite images. It also reviews publicly available data, metrics for evaluation and recent advances in self-supervised and foundation model methods. Different challenges like computational complexity, lack of annotations, domain shift, and lack of benchmarks are discussed. In conclusion, the future research directions encompass efficient integration of TSFM prototype, multimodal learning, and explainable AI in precision agriculture systems to address the challenges of scalability and precision. The purpose of this work is to offer a structured overview to inform researchers to build strong, data-efficient and generalizable crop monitoring models for real-world agricultural decision-making across a variety of environmental conditions and to aid sustainable food security and policy planning around the world.

Keywords:- Few-shot learning, Crop type recognition, Time-series foundation models, Prototype adaptation, Remote sensing

Introduction

The recognition of the crop type is a fundamental component when considering precision agriculture, which is able to benefit from the applications of crop monitoring, yield forecasting, food security assessment, agricultural policy measures and sustainable land-use management. With the new satellites like Sentinel-1, Sentinel-2 and Landsat, the remote sensing of agricultural landscapes has become large-scale and cost-effective. The temporal, spectral and spatial information offered by these sensors can be used to differentiate crop type by their phenological growth pattern during the crop life cycle [2] [3].

In recent years, the accuracy of crop classification systems has been greatly enhanced by the accomplishments of machine-learning and deep-learning technologies. Support Vector Machines (SVMs), Random Forest (RFs) and Decision Trees are machine learning techniques that have been extensively employed for crop mapping. However, these approaches are based on handmade features and have very poor generalization properties in heterogeneous agricultural fields [1]. To overcome these limitations, deep learning networks like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks and Transformer based models have been developed to automatically extract discriminative features from time-series data derived from remote sensing [5].

Although they are successful, most current crop classification models have the requirements that there is a considerable amount of labeled data and that the training and testing sets come from the same geographic area. In reality, these assumptions are not always true. There are also marked differences in the climate, soil characteristics, agronomic practices, watering systems, and crop programs in agricultural areas. As a consequence, models trained in a region different from the one where they are deployed are likely to experience significant performance drop when they are used in the new region, given domain shift and distribution mismatch [7]. Moreover, the gathering and annotation of crop labels for each new region is expensive, time consuming and sometimes unfeasible, especially in developing countries. To address these problems, researchers have turned to the study of few-shot learning methods that seek to attain the best possible classification performance with only a few examples drawn from the target domain that are labeled for the task. Few-shot learning methods aim to transfer knowledge acquired from source domain(s) to new target domain(s) where training data is limited or non-existent [8]. In this sense, prototype based learning is one of the most promising paradigms, which involves the building of representative class prototypes and their adaptability as a method to enhance class classification in low data conditions [6].

In recent years, Foundation Models (FMs) have revolutionized multiple domains of artificial intelligence (AI) by learning abstract representations from vast amounts of data. More recently, Foundation Models (FMs) have caught the imagination of multiple artificial intelligence (AI) domains, learning abstract representations from large data sets. Following the success of large-scale pre-training in NLP and computer vision, Time-Series Foundation Models (TSFMs) have been introduced to learn universal temporal patterns from various types of time series data. The models show high transferability and adaptability, especially for heterogeneous environments and limited annotations typically found in agricultural applications [9] [10].

With the continuing increase of research in this area, a comprehensive survey is needed to bring together the existing knowledge and point to future opportunities. This survey summarizes the development of the crop type recognition techniques, and focuses on few-shot learning, cross-region adaptation, time-series foundation models, prototype-based approaches. In addition, it reviews publicly available data, the various metrics for evaluating the system and existing issues, as well as new directions in the research. The survey aims at giving a systematic overview of the state of the art and contributing to the development of scalable, robust, and data efficient crop type recognition systems, which can be used for future research and application by researchers and practitioners.

2. Background and Related Concepts

2.1 Crop Type Recognition Using Remote Sensing

Crop type recognition is one of the most important applications of remote sensing in precision agriculture which allow the large scale monitoring of agricultural lands, the inventory of the crops, the estimation of yield and the assessment of food security. Sentinels 1, 2 and Landsat are modern Earth observation satellites that deliver high temporal and high spectral resolution data, which has the potential to be used for crop type discrimination using the different phenological growth behaviours of the various crops. While traditional crop classification approaches were based on handcrafted features and machine learning algorithms, more recent works use deep learning models that are able to learn automatically discriminative representations from time-series and satellite imagery [8].

2.2 Few-Shot Learning

Few-Shot Learning (FSL) is a machine learning paradigm to deal with a situation with only a few labeled samples. The goal of FSL is to learn transferable knowledge from source domains and quickly transfer knowledge to new target domains with few examples, in contrast to traditional supervised learning approaches that need large amounts of labeled data. Labeling data for crops is not only costly in agriculture but also may be time consuming, especially in different geographic areas. Thus, FSL has appeared to be an effective solution to crop classification in situations where data is scarce[9]. Typical FSL methods include metric-based learning, optimization-based learning, and meta-learning methods, which emphasize the issue of improving the generalization ability in the presence of only limited supervision.

2.3 Time-Series Foundation Models

Large-scale pre-trained models that are able to learn a generalized representation from a large amount of data and transfer it to different tasks are known as Foundation Models (FMs). To process sequential and temporal data, inspired by the success of foundation models in natural language processing and computer vision, Time-Series Foundation Models (TSFMs) have recently been developed. These models utilize self-supervised learning and large-scale pre-training to learn universal temporal patterns, trends and dependencies. For agricultural use, TSFMs can be used to model the dynamics of crop growth from multi-temporal satellite image sequences which can be used to robustly extract features and generalize for other regions and environmental conditions[10]. They are especially well suited for applications of cross-region crop type recognition, where there is a shortage of labeled data.

2.4 Prototype Adaptation

Prototype adaptation is a few-shot learning method where each class is represented by a "prototype" which is generally the center of the feature embedding space of the class members. In the classification, unlabeled samples are classified to the class whose prototype is closest to it in the learned feature space. Prototypical Networks and its variants have shown good performance in low data scenarios because of its simplicity and effectiveness. For cross-region crop recognition, prototype adaptation techniques are used to refine class prototypes based on a small number of samples from the target domain, which helps to minimize the effect of domain shifts due to differences in climate, soil properties, and crops' cultivation. Such methods are iterative, adjusting prototypes to the target environment to enhance the robustness of the classification and facilitate transfer of knowledge from one region to another[9] [10].

2.5 Relationship Between TSFMs and Prototype Adaptation

The application of few-shot cross-region crop type recognition based on Time-Series Foundation Models and Prototype Adaptation is a promising approach. The prototype adaptation learns to quickly adapt to new regions with a few labeled samples, whereas TSFMs learn generalized temporal representations from the large-scale agricultural datasets[10]. These methods together solve two key problems with agricultural remote sensing, which are the lack of labelled data and the large geographical variation in domain shifts. Therefore, TSFMs and prototype-based learning have become an effective way to build scalable, data-efficient and transferable crop classification systems.

3. Literature Survey

Crop type recognition systems have been advanced greatly by recent improvements in the fields of remote sensing, machine learning and artificial intelligence. The current strategies fall into two groups: traditional machine learning methods, deep learning techniques, few-shot learning techniques, and new foundation model-based approaches. The major development in these areas and their contribution to the cross-region crop classification are briefly reviewed here.

Table 1. Comparative Analysis of Existing Studies

Author(s)	Dataset	Method	Key Findings
Ma et al. (2019)	Multi-Temporal Remote Sensing Data	Deep Learning Framework	Showed that deep architectures improve feature extraction and classification performance.
Pelletier et al. (2019)	Sentinel-2 Dataset	Temporal CNN (TempCNN)	Effectively captured crop phenological patterns and outperformed traditional methods.
Wang et al. (2020)	Multiple Benchmark Datasets	Few-Shot Learning Survey	Identified metric-based and meta-learning approaches as effective solutions for limited labeled data scenarios.
Garnot & Landrieu (2021)	PASTIS Dataset	Satellite Image Time-Series Transformers	Demonstrated the effectiveness of transformers in modeling long-range temporal dependencies.
Xu et al. (2022)	Sentinel-1 & Sentinel-2	Cross-Domain Transfer Learning	Reduced performance degradation caused by regional domain shifts in crop classification.
Jean et al. (2023)	Multi-Region Agricultural Datasets	Meta-Learning for Crop Classification	Improved adaptation to unseen regions using limited target-domain samples.
Zhou et al. (2023)	EuroSAT and Sentinel Time-Series Data	Prototype-Based Domain Adaptation	Enhanced cross-region classification through adaptive prototype learning.

Goswami et al. (2024)	Multiple Time-Series Benchmarks	Time-Series Foundation Models (TSFMs)	Demonstrated strong transferability and generalized representation learning capabilities of TSFMs.
Das et al. (2024)	Agricultural Time-Series Datasets	Self-Supervised Time-Series Learning	Reduced dependence on labeled crop data through large-scale self-supervised pretraining.
Yekeen et al. (2025)	Public Time-Series Benchmarks	TSFM Survey and Benchmark	Established TSFMs as state-of-the-art models for temporal analysis and classification tasks.
Li et al. (2025)	Sentinel-2 Multi-Region Dataset	Foundation Model + Few-Shot Adaptation	Improved cross-region crop recognition using pre-trained temporal representations.
Zhang et al. (2025)	Agricultural Remote Sensing Dataset	Prototype Adaptation Network	Achieved superior classification performance with limited target-region samples.

Table 2 demonstrates the research trend between 2016 and 2025, where the recognition method for crops has changed from traditional machine learning and domain adaptation to deep learning and transformer-based architectures, as well as few-shot learning. First, handcrafted feature extraction and supervised classification methods were the focus of early studies, and later automated feature learning and temporal modelling using deep neural networks were the focus of later research. With the advent of Time-Series Foundation Models (TSFMs) and self-supervised learning from 2024, research has turned to more general representations learning and cross-region adaptability.

Table 2. Research Trends of last 10 years [2016 to 2025]

Year Range	Major Research Direction
2016–2018	Traditional Machine Learning and Domain Adaptation
2019–2021	Deep Learning and Transformer-Based Crop Classification
2022–2023	Few-Shot Learning and Prototype Adaptation
2024–2025	Time-Series Foundation Models and Self-Supervised Learning

4. Research Gaps

There are some key issues and research needs in few-shot cross-region crop type recognition as shown in Table 2. Climate, soil and agricultural changes have a major impact on model generalization across regions due to domain shifts. Few of the agricultural datasets are labelled, further reducing the power of data-hungry deep learning models. While both Time-Series Foundation Models and prototype adaptation techniques have demonstrated potential, there is a lack of studies that incorporate both models. Moreover, consistent standards, interpretable AI models, and models that are efficient in computation are needed to support the classification of crops in real-word agricultural contexts at large scale and with high reliability.

Challenges	Research Gaps
Domain shift across geographical regions	Lack of standardized benchmarks for few-shot cross-region crop recognition
Limited labeled agricultural datasets	Limited integration of TSFMs with prototype adaptation
High computational cost of foundation models	Insufficient studies on lightweight and efficient models
Variability in crop phenology and environmental conditions	Lack of robust cross-region evaluation protocols
Poor interpretability of AI models	Limited research on explainable crop classification systems

Feature distribution mismatch between regions	Need for adaptive and dynamic prototype learning mechanisms

5. Conclusion and Future works

In this survey, recent developments in few-shot cross-region crop type recognition are explored and the importance of TSFMs and prototype adaptation techniques are highlighted. The review pointed out the shift of traditional machine learning and deep learning methods to foundation model-based approaches to learn transferable temporal representations from massive remote sensing data. Current research has shown that few-shot learning and prototype-based approaches are effective at decreasing the need for large amounts of labeled data, and enhance adaptation to geographically varied areas. Although these advances have been made, there remain difficulties, including domain shifts, small amounts of data with annotations, computational complexity, and insufficient standardized benchmarks, that have made broad use difficult. For future work, we suggest the creation of agriculture-specific foundation models, the fusion of TSFMs with adaptive prototype learning, and the use of self-supervised learning to further enhance generalisation. Moreover, the multimodal data fusion, explainable AI, and lightweight deployment strategies should be explored to ensure that crop monitoring systems are scalable, robust, and practical. The directions could make significant strides in the advancement of intelligent and data-efficient precision agriculture.

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