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Vegetation Phenology Assessment using Artificial Intelligence: A Survey

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Abstract: Vegetation phenology plays a pivotal role in understanding ecosystem dynamics, biodiversity, and climate change impacts. Remote sensing data offers a powerful toolset for monitoring, mapping, and modelling vegetation phenology at various spatial and temporal scales. This paper reviews the methodologies and advancements in vegetation phenology studies using Artificial Intelligence techniques.

Keywords: vegetation phenology, remote sensing, monitoring, mapping, modelling, temporal analysis, spatial analysis, environmental factors, ecological modelling.

1.0 Introduction

Vegetation phenology defines physiological development stages of crop growth from planting to harvest. Crop growth management and yield estimation require accurate crop phenology information during the growing season. For example, water stress in different crop growth stages may affect crop yield differently. For this reason, irrigation maybe scheduled depending on the crop growth stage. Some crop growth stages, such as the latter part of the reproductive growth stages for soybeans and the earlier tasselling period for corn, are more beneficial for irrigation application. Crop phenology can also be used for fertilization scheduling, pest management, and harvesting operation. Crop phenology and growth condition provide information for crop growth modelling and yield estimation.

Agricultural productivity and food security are critically dependent on precise crop management and monitoring. Understanding crop phenology—the study of the timing of crop life cycle events—and accurately mapping crop types across large agricultural landscapes are fundamental for optimizing yield, managing resources, and mitigating the impacts of climate variability.

Traditional methods for crop monitoring rely on field surveys and manual observations, which are time-consuming, labour-intensive, and often limited in scope. The advent of remote sensing technologies has revolutionized agricultural practices by providing large-scale, high-resolution data on crop health and development. However, the sheer volume and complexity of this data necessitate advanced analytical techniques to extract meaningful insights efficiently.

Deep learning, a subset of artificial intelligence (AI) that mimics the human brain's neural networks, has emerged as a powerful tool for analysing vast amounts of remote sensing data. By leveraging deep learning algorithms, researchers can automate the processes of crop mapping and phenology estimation with unprecedented accuracy and speed. These algorithms are capable of learning intricate patterns and relationships within the data, making them ideal for handling the variability and complexity inherent in agricultural landscapes.

2.0 Literature Review

In this section state of the art research work in the area of vegetation phenology using deep learning and machine learning has been explored.

2.1 Deep Learning Technique used for vegetation phenology –

Deep Learning is a method in artificial intelligence (AI) that teaches computer to process data in a way that is inspired by the human brain. Deep learning models can recognize complex patterns in pictures, text, sound and other data to produce accurate insights and prediction. Deep learning is sub set of machine learning that uses multi-layered neural network, to simulate the complex decision- making power of the human brain.

1. Teodoro et.al. (2024) has proposed a CNN Model for Bean Phenology Classification Using Transfer Learning Techniques. This method is significant for monitoring crop pattern changes, estimating crop yields, and issuing crop safety warnings, making it highly valuable for precision agriculture. Ewa panek-Chwastyk et.al.(2024) has proposed Time Series from Sentinel-2 for Organic Durum Wheat Yield Prediction Using Functional Data Analysis and Deep Learning Applying functional data analysis and deep learning techniques to time series data for Organic drum wheat yields insightful predictions, leveraging the temporal patterns within the dataset.Nicolas Younes et.al.(2020)All models of satellite-derived phenology are wrong , but some are useful : A case study from northern Australia. Jianing Shen et.al.(2024) The paper on mapping maize planting density using UAV multispectral remote sensing and deep learning technology presents a method to accurately estimate planting density Mapping Maize Planting Densities. Sajjad Hussain et.al.(2023) examines the relationship between land surface temperature (LST) and various vegetation indices using multitemporal remote sensing data in the Sialkot region of Pakistan. It highlights how different vegetation indices correlate with LST, offering insights into environmental monitoring and agricultural management by understanding the impact of vegetation on surface temperature dynamics. Rik J.G. et.al.(2023).focussesed on estimating fine-scale vegetation distribution using imagery generated from Remotely Piloted Systems (RPS) and structural data. It highlights how high-resolution RPS imagery and structural metrics can enhance restoration monitoring by providing detailed and accurate vegetation distribution maps, improving the effectiveness of ecological restoration efforts.Joao P.S. et. al.(2024) focussed on mapping integrated crop-livestock systems using a fusion of Sentinel and Planet Scope time series data. By leveraging deep learning algorithms, the study aims to improve the accuracy and temporal resolution of land use classifications within these systems. Xiangyu Lu et.al./(2023)has presented a method for automated rice phenology stage mapping using UAV imagery combined with deep learning algorithms. This approach enhances the precision and efficiency of identifying different growth stages of rice crops. Xiao Kun et.al.(2023) focussed on Mapping fine-spatial-resolution vegetation spring Phenology from individual Landsat images using a convolutional neural network.It hightlights the CNN's capability to accurately identify phenological stages by extracting and analysing features from high-resolution remote sensing data, improving the precision of vegetation monitoring.Yue Qu et. al. (2024) Estimated Inter annual Monitoring of Cropland in South China from 1991 to 2020 Based on the Combination of Deep Learning and the LandTrendr Algorithm highlights the effectiveness of integrating advanced machine learning techniques with land use models to track and analyze changes in cropland over three decades, providing valuable insights into agricultural dynamics and land management practices in the region.Haseeb Rehman Khan et. al. (2023)has demonstrated how advanced deep learning models can effectively classify different crops at an early stage, leveraging the high temporal resolution of Sentinel-2 data to support timely agricultural decision-making and improve crop management for smallholder farmers. Leandro et.al.(2023) has utilized computer vision and deep learning to dynamically classify phenological stages in vegetable crops. It aims to improve to classification accuracy by leveraging advanced neural network techniques and multi-temporal satellite. No-Wook et.al.(2023) has incorporated Deep Learning-Based Virtual Optical Image Generation and Its Application to Early Crop Mapping. This study develops a deep learning-based approach for generating virtual optical images and applies it to early crop mapping. By simulating optical imagery, it aims to

improve the timeliness and accuracy of crop mapping, aiding in early-season agricultural management decisions.

2.2 Machine learning technique used for vegetation phenology

Machine learning is a field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalization unseen data and thus perform tasks without explicit instruction. Machine Learning is a branch of artificial intelligence (AI) and computer science that focuses on the using data and algorithms to enable AI to imitate the way that humans learn, gradually improving its accuracy.

Cenhanyi et.al.(2024) has estimated Crop Yield Anomalies for 2022 in Ukraine Based on Copernicus Sentinel-1, Sentinel-3 Satellite Data, and ERA-5 Agrometeorological Indicators. This method is significant for monitoring crop pattern changes, estimating crop yields, and issuing crop safety warnings, making it highly valuable for precision agriculture. . Atiya Khan et.al.(2024) has proposed A Novel Approach to Mapping the Spatial Distribution of Fruit Trees Using Phenological Characteristics mapping the spatial distribution of fruit trees for agricultural management, yield estimation ,and ecological studies. Xinyi Gao et.al./(2024) used to Comparison of Cloud-Mask Algorithms and Machine-Learning Methods Using Sentinel-2 Imagery for Mapping Paddy Rice in Jianghan Plain.The findings suggest that machine learning-based cloud masking significantly enhances the precision of paddy rice mapping in regions with frequent cloud cover. Adriano has used (2024) Mapping Crop Types At a 10 m Scale Using Sentinel-2 Data and Machine Learning Methods Applying functional data analysis and deep learning techniques to time series data for Organic drum wheat yields insightful predictions, leveraging the temporal patterns within the dataset. Zhangxin et.al.(2024) has focused This study estimates rice yield in Jiangsu, China, using multi-temporal remote sensing data combined with machine learning algorithms. It aims to enhance the accuracy of yield predictions through advanced analysis of temporal satellite imagery. Jinxi Yao et.al.(2022) has proposed The Classification Method Study of Crops Remote Sensing with Deep Learning, Machine Learning, and Google Earth Engine .It aims to assess the effectiveness of combining these technologies for accurate and efficient crop mapping, offering insights into optimal methodologies for agricultural monitoring. Savittri et.al. (2024) has used to Estimating Sugarcane Aboveground Biomass and Carbon Stock Using the Combined Time Series of Sentinel Data with Machine Learning Algorithm .This study estimates sugarcane above- ground biomass and carbon stock by combining time series data from Sentinel satellites with machine learning algorithms. It aims to enhance the accuracy and efficiency of biomass and carbon stock assessments for sustainable agricultural practices. Mo Wang et.al./(2024) incorporated A Comprehensive Evaluation of Dual-Polarimetric Sentinel-1 SAR Data for Monitoring key Phenological Stages of Winter Weate. The study demonstrates that dual-polarization metrics can effectively distinguish between different growth stages, enhancing the accuracy of agricultural monitoring. The findings highlight the potential of SAR data for precise crop phenology assessment in precision agriculture. .Li Wen et.al./(2023) Focused to Improved Wetland Mapping of a Highly Fragmented Agricultural Landscape Using Land Surface Phenological Features. The approach improve accuracy by integrating multi temporal remote sensing data and machine learning algorithms, effectively distinguishing wetlands from surrounding agriculture fields. Anne Gobin et.al.(2023)has incorporated Crop Phenology Modelling Using Proximal and Satellite Sensor Data. This research models crop phenology using both proximal and satellite sensor data. By integrating data from multiple sources, it aims to enhance the accuracy of crop growth stage predictions , facilitating better decision-making in agricultural management. Andualem et.al. (2022) Enhancing Smallholder Wheat Yield Prediction through Sensor Fusion and Phenology with Machine Learning and Deep Learning Methods.This research focuses on enhancing smallholder yield prediction through sensor fusion and phenology using machine learning and deep learning method.Yahui Guo et.al.(2022) has estimated for Comparison of Multi-Methods for Identifying Maize Phenology Using PhenoCams This study compares multiple methods for identifying maize phenology using phenocams. Md. Didarul (2023) Estimated Using Integrated Remote Sensing and Meteorological Data and Machine Learning. This study focuses on rapid rice yield estimation by integrating remote sensing, meteorological data, and machine learning techniques. By combining these datasets and methods, it aims to provide timely and accurate predictions of rice yield, facilitating effective agricultural management decision.

Emine Senkardesler et.al.(2023) has proposed Integration of Object-Oriented Remote Sensing and Machine Learning to Create Field Model for Optimized Regional Agricultural Management. This approach enhances precision in monitoring crop health, yield prediction, and resource allocation, ultimately improving agricultural efficiency and sustainability. Liusheng Han et. al. (2024). A novel approach to mapping the spatial distribution of fruit trees using phenological characteristics leverages remote sensing data to identify and classify fruit tree species based on their distinct growth stages. This method improves accuracy in detecting and monitoring fruit tree distributions, aiding in better agricultural planning and resource management.

3.0 Performance Analysis

In this section the performance analysis of deep learning and machine learning technologies has been compared in terms of Accuracy, RMSE,MSE and correlation coefficient.

3.1 Performance Analysis of Deep Learning For vegetation phenology

The performance of deep Learning for vegetation phenology involves evaluating various aspects, such as accuracy, model architecture, data sources, and practical application.

SNo	Author/Publisher	Journal	Year	Area of Research	Technologies/Data set	Findings
1.	Teodoro et.al./MDPI	AgriEngineering	2024	Phenology(Beans)	CNN/field survey data	Accuracy of 96.71%
2.	EwaPanek et.al./MDPI	Sensor	2024	Crop Yield Prediction	Extreme Gradient Boosting/Sentinel-1 & Sentinel-3.	50% compared to previous year.
3	Nicolas et.al./Elsevier	International Journal of applied Earth oservation and geoin	2021	Phenology	Cloud Mask /Sentinel-2 and MODIS	Accuracy of 81%
4.	Jianing et.al./MDPI	Drones	2024	Crop Mapping (maize)	YOLO,GLSM/UAV	Accuracy of 95.8%
5.	Sajjad Hussain et. al./springer	Geoscience Letters	2023	Crop Growth	CNN, ResNet and L-TAE /Landsat	Accuracy of 89.96
6.	Rik J.G. et. al./Elsevier	Science of remote sensing	2023	vegetation distribution	DAP/UAV	Accuracy of 79%
7.	Joao P.S. et. al./MDPI	Remote Sensing	2024	Mapping Integrating Crop	ICLS/Sentenal-2, planet scope	Accuracy 0f 91%
8.	Xiangyu Lu et.al./MDPI	Drones	2023	Phenology(Rice)	DL algorithm/UAV	Accuracy of 90%

9.	Nagai Shin et.al/Wiley	Ecological Research	2023	Plant phenology(East Area)	SensorTechnology/ MODIS	R^2=0.86, RMSE=9.61
10.	Xiao Kun et.al./Taylor &Francis	Remote Sensing	2023	Monitoring & Mapping Vegetation	VGD, CNN/ Landsat ,MODIS	Accuracy= 84.6%
11.	Yue Qu et. al./MDPI	International Journal of Applied Earth Observation and Geo information	2024	Crop Land Monitoring	DLwith LandTrendr/ LandSat	Wheat Field =68%
12.	Haseeb et.al./MDPI	Sensors	2023	Crop Mapping	LSTM/Sentinel-2	OA of 0.91-0.93
13.	Leandro et.al./MDPI	Agronomy	2023	Rice Yield Estimation	Customized ML/NDVI	R2=0.92,RMSE=0.93
14.	Emine et.al./MDPI	Environmental Sciences Proceeding	2023	Vegetable Crop Phenology	SSD,YOLO/Computer Data	Accuracy= 92%
15.	No-Wook Park et. al./MDPI	Applied Science	2023	Crop Mapping	CNN,RF/Sentinel-2,SAR,NDVI	Accuracy >90%

3.2 Performance Analysis of Machine Learning For vegetation phenology

Performance analysis for machine learning for vegetation phenology involves evaluating how effectively different algorithms can predict and classify phenological stages of vegetation based on remote sensing data.

SNo	Author/Publisher	Journal	Year	Area of Research	Technology/Data Set	Findings
1.	Cenhanyi et.al./MDPI	Remote Sensing	2024	Crop Mapping(Maize)	4Model ML/NDVI,NMP,SLN	NSE=0.97,RMSE= 1.55
2.	Yilin Mao et.al./IEEE	Applied Earth Observatio &Remote Sensing	2024	Ecological Index (tea)	RFR,SVR /Landsat, Sentinel-2, UAV images	Accuracy of 95.5%
3.	Atiya Khan et.al/MDPI	International Journal of Computing and Digital System	2024	Crop Mapping	Random Forest, Support Vector Machines (SVM), and Neural Networks/Temporal data	Accuracy of 97.6%
4.	Xinyi Gao et.al. /MDPI	Remote Sensing	2024	Rice Mapping	Cloud–Mask with ML/Sentinel	$R^2 > 0.8$
5.	Adriano et.al./MDPI	Agronomy	2024	Wheat yield prediction	CNN, RNN/NDVI,NDRE	Accuracy of 76%
6.	ZhonglinJi et. al./Elsevier	Ecological Indicators	2024	Crop Yield	CNN-LSTM/MODIS	Accuracy of 98%
7.	Jinxi Yao et.al./MDPI	Remote Sensing	2022	Crop Classification	DNN/Sentinel and Landset	Accuracy of 76%
8.	Savittri et.al./MDPI	Remote Sensing	2024	Crop Mapping	RFR,SVR/Sentinel-1,Sentinel-2	Recall =0.834 Precision=0.835
9.	Mo Want et.al/MDPI	Remote Sensing	2024	Monitoring Phenological stage(Wheat)	Polarimetric Decomposition/Sentinel-1 SAR	Accuracy= 86%
10.	Li Wen et.al./MDPI	Remote Sensing	2024	Wetland classification & mapping	Random Forest,Bench Mark Experiment/Sentinel-2	F1 > 0.8
11.	Anne Gobin et.al./MDPI	Remote Sensing	2023	Crop Phenology Modelling	BV-NET/VI,NDVI	Wheat Field of 68%
12.	Andualem et.al./MDPI	Agriculture	2022	Crop Phenology	CNN,DNN/Sentinel-1,Sentinel-2	RMSE= 0.84-0.97
13.						

14.	Yahui Guo et. al./MDPI	Remote Sensing	2022	Maize Phenology	Savitzky, HUNTs/MODIS	R2=0.92,RMSE=0.93
15.	Md Didarul et.al./MDPI	Remote Sensing	2023	Rice Yield Estimation	Customized ML/MDVI	Accuracy= 92%
	Liusheng et.al./MDPI	Agronomy	2024	Fruit Trees Phenology	CNN,ANN/Sentinel-1,SAR	Accuracy= 90.34%

4. Conclusion and Future Work

Vegetation phenology plays a crucial role in understanding ecosystem processes and climate interactions. The use of remote sensing data for mapping, monitoring, and modeling vegetation phenology has proven to be highly effective due to its capability to provide continuous, large-scale observations. Combining multispectral and multitemporal remote sensing data improves the accuracy of phenological models. This integration allows for more precise identification of phenological events such as leaf-out flowering, and senescence. he development of advanced algorithms, including machine learning techniques and Deep Learning has improved the accuracy of phenological predictions. These models can better account for environmental variables and anomalies, leading to more robust phenological assessments. Deep learning technique such as out perform the performance of machine learning techniques in term of accuracy.

Future research should focus on enhancing the temporal resolution of remote sensing data to capture rapid phenological changes. This can be achieved by integrating data from multiple satellite sources and incorporating UAV (drone) observations.

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