DEEP LEARNING-BASED SEASONAL NDVI FORECASTING FOR ENHANCED AGRICULTURAL SUSTAINABILITY: A CASE STUDY IN THE KUTTANAD REGION, KERALA, INDIA

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ABSTRACT

India's agricultural sector, despite transitioning across economic domains, remains heavily reliant on its agrarian foundation, which faces substantial challenges from natural and human-induced disruptions. Leveraging technological advancements such as Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning holds immense promise in bolstering agricultural productivity by providing actionable insights. This study focuses on harnessing Deep Learning techniques to forecast seasonal Normalized Difference Vegetation Index (NDVI) in paddy fields using satellite imagery and an in-depth analysis of paddy field health based on the predicted NDVI values with a specific emphasis on the Kuttanad region in Kerala, India. Integration of Deep Learning models, particularly Long Short-Term Memory (LSTM) networks, the research aims to deliver precise and timely predictions of NDVI, facilitating a holistic evaluation of crop health dynamics. Time series satellite imagery with optimal temporal resolution and suitable spectral bands for NDVI computation is utilized for analysis. The results demonstrate the effectiveness of LSTM models in accurately predicting seasonal NDVI. The predicted NDVI values are correlated with ground truth data, allowing for a comprehensive assessment of paddy field health. The developed model demonstrated superior performance, achieving notable accuracy of an R^2 value of 0.978. Comparing anticipated NDVI values to benchmarked periods of optimal vegetation health, one can assess the current state of crops and predict future trends in vegetation conditions.

Keywords: Deep Learning, Machine Learning

1. INTRODUCTION

A zenithal view and comprehensive information on earth surface have been provided by the advent of satellite remote sensing technology. Over recent decades the foot prints of satellite imagery have been in every domain, so as it become instrumental in identifying various characteristics of soil and crops, which leads to the advancements in sustainable agricultural management [1][2]. These techniques have significantly reduced the human efforts in identifying the crop health and cropping patterns as various crop related parameters and indices can be estimated from these technologies. Normalized Difference Vegetation Index (NDVI), a quantification of live green vegetation in an area based on the difference between near-infrared (NIR) and red light reflected by plants [3], which is a widely used metric in remote sensing to identify vegetation health and density is a prominent example. The index is calculated as the ratio between the Top of Atmosphere (TOA) reflectance of the red band and the near-infrared (NIR) band. This differentiation allows to distinguish between densely vegetated areas, which exhibits positive NDVI values as compared to water or built-up areas, whose values are negative or close to zero. As NDVI provides crucial information about the health, vigor and

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distribution of vegetation, it is considered as one of the key tools in remote sensing [4] and is widely used for vegetation monitoring [5].

$$\text{NDVI} = \frac{(NIR+RED)}{(NIR-RED)}$$

Evaluation of crop health and productivity is an essential part in sustainable agriculture, at the same time there is an inherent and complex spatial and temporal dynamic in it. This study addresses the inclusion of deep leaning based techniques applied to time-series satellite imagery to overcome the short comings of traditional NDVI prediction methods due to these complex dynamics. The core issue at hand is the lack of precise tools for forecasting seasonal NDVI variations in paddy fields, which hampers farmers and agricultural stakeholders from making informed crop management decisions.

The proposed deep learning approach aims to provide a more robust and efficient solution for NDVI forecasting, thereby advancing precision agriculture and promoting sustainable paddy cultivation. By integrating cutting-edge machine learning algorithms with high-resolution satellite data, this study seeks to enhance the accuracy of NDVI predictions, offering a significant improvement over traditional method. This advancement will empower farmers with better insights into crop health, enabling more effective management practices and ultimately contributing to increased agricultural productivity and sustainability. This approach aims in providing more robust, effective and efficient method for NDVI forecasting, which can backup precision agriculture and promoting sustainable paddy cultivation. A significant improvement over the traditional methods can be obtained with the combination of machine learning algorithms and high-resolution satellite imageries. Increased agricultural productivity and sustainability can be achieved, as this method provides better insights into crop health and in formulating better management practices.

2. MATERIALS AND METHODS

2.1 Study Area

Kuttanad, an area in the Indian state of Kerala that includes the districts of Alappuzha, Kottayam, and Pathanamthitta, is well-known for its enormous rice fields and unique geological features. It is one of the few places in the world where farming is done between 1.2 and 3.0 meters (4 and 10 feet) below sea level. As the state's principal rice producer, Kuttanad has a significant historical significance in South India's prehistoric past. The Kuttanad farming system was designated as a Globally Important Agricultural Heritage System (GIAHS) by the Food and Agriculture Organisation (FAO) in 2013. The study area was selected from the R-block of Kuttanad region, with an area of 9.35 sq.km, Figure 1.

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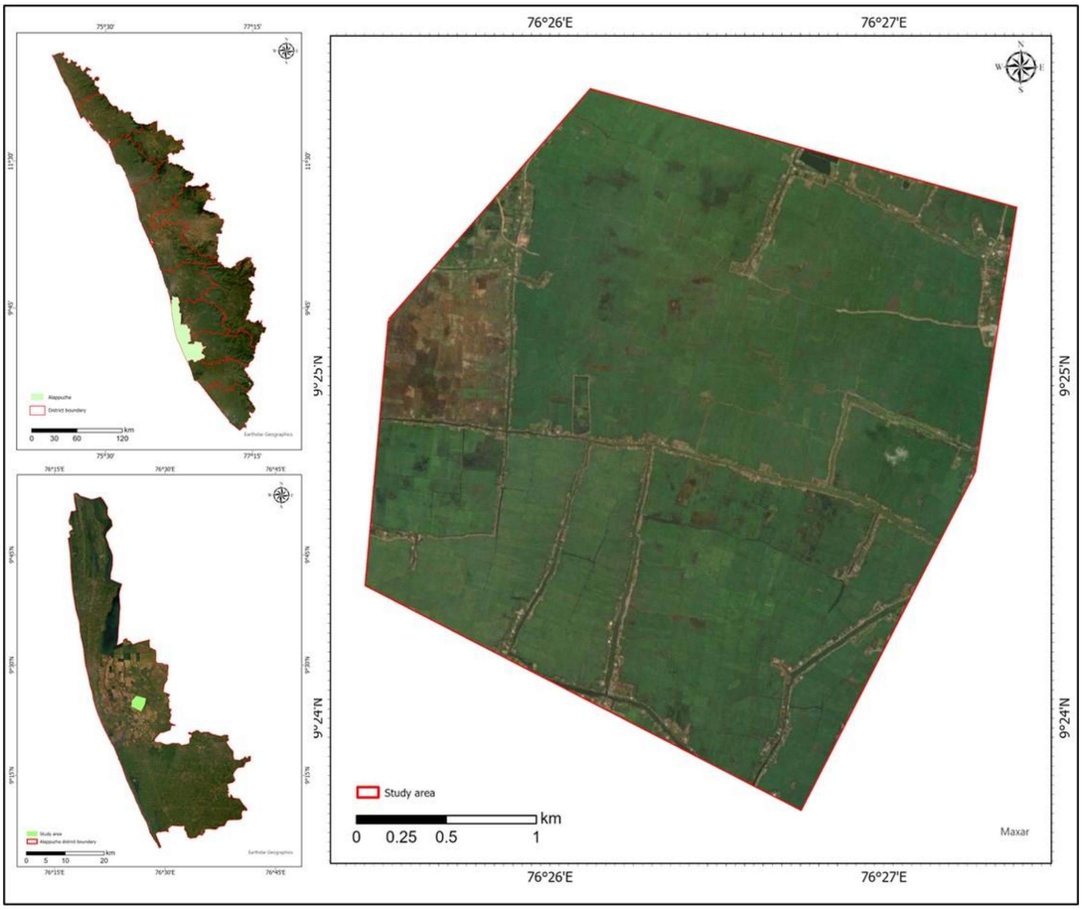

Figure 1. Study Area in the Kuttanad Region

2.2 Dataset

The satellite imagery used for the study area of region of Kuttanad spans from August 2018 to January 31, 2024. This data is sourced from the Copernicus Sentinel-2 mission's COPERNICUS/S2_SR_HARMONIZED dataset, as detailed in Table 1. Accessible via the Google Earth Engine (GEE) platform, the Copernicus program's Sentinel-2 satellites provide unrestricted Earth observation data essential for applications such as disaster relief, environmental monitoring, and climate change analysis.

Table 1. Description of Sentinel data

Aspect	Description
Mission	The Sentinel-2 program, comprising the Sentinel-2A and Sentinel-2B satellites, aims to acquire high-resolution multispectral imagery of the Earth's surface collectively.
Instrument	The Multi-Spectral Instrument (MSI) onboard captures data across 13 spectral bands, encompassing wavelengths from the visible to the short-wave infrared.
Data Type	Sentinel-2 Level-2A data was utilized to generate the surface reflectance imagery comprising the Copernicus/S2_SR_HARMONIZED dataset available on Google Earth Engine.
Data characteristics	As the data is cleansed of atmospheric and geometric distortions, it is appropriate for quantitative analysis and cross temporal comparison.
Data quality	Over a range of temporal and spatial extents, the harmonized dataset offers surface reflectance values that are calibrated and consistent.
Resolution	The dataset offers high spatial resolution, ranging from 10 to 60 meters depending on the spectral band and processing level.
Application	Highly beneficial for various applications, including vegetation analysis, change detection, land cover categorization, and environmental monitoring.

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2.3 Tools Used

The prominent cloud-based platform Google Earth Engine (GEE) which allows to access, analyze and visualize has been used for the data processing and analysis, as it supports the processing of bulk data without requiring substantial computational resources. In this study, Python API is employed within GEE for data preprocessing and modeling tasks. The libraries that are used for the analysis are, Geopandas, a library supporting geographic operations and data structures, allowing users to handle geographic data files like shapefiles and GeoJSON. Pandas a widely-used Python module for data manipulation, offering DataFrame and Series data structures ideal for working with tabular and structured data. Numpy an essential Python package for numerical computations, providing support for matrices, multidimensional arrays, and efficient mathematical operations. Matplotlib a Python library for static, interactive, and publication-quality visualizations, used in exploratory data analysis and research presentation. Geemap a python library for interactive mapping and data visualization in Jupyter Notebooks, integrating with Google Earth Engine (GEE) for accessing and visualizing satellite imagery and geospatial data. Ipygee a python module enabling Google Earth Engine (GEE) usage within Jupyter Notebooks, facilitating data query, analysis, and visualization workflows seamlessly. Sktime is a python machine learning library that is for time series forecasting and analysis and provides a unified interface for the development, evaluation, and deployment of forecasting models. Keras is a high-level neural network API in Python, compatible with TensorFlow, Theano, or Microsoft Cognitive Toolkit (CNTK), which can be used for the development of different deep architectures like CNNs, RNNs, LSTMs.

2.4 LSTM Model

A particular kind of recurrent neural network (RNN) architecture called a Long Short-Term Memory (LSTM) model was created to get over the drawbacks of conventional RNNs in terms of identifying long-term dependencies in sequential input [6]. Sequence prediction, time series forecasting, natural language processing, and other sequential data-related tasks are especially well-suited applications for LSTMs. LSTM stands out from traditional neural networks by processing entire data sequences, not just individual points. This capability, facilitated by memory cells and gates, enables LSTM to capture long-term dependencies in data sequences. Memory cells store and transfer information over time, controlled by gates that manage data input, retention, and output. The model's hidden state carries information across time steps, crucial for identifying sequential patterns. LSTM is trained using backpropagation through time, optimizing parameters with methods like Adam or SGD. Overall, LSTM excels in uncovering temporal patterns in data, vital for various AI and machine learning applications.

2.5 Architecture

The procedure begins by importing the necessary libraries essential for executing, subsequently, the shapefile delineating Kuttanad is read to facilitate the retrieval and refinement of Copernicus Sentinel-2 satellite imagery data based on predefined spatial boundaries, and thresholds for cloud cover (less than 10%). Following this stage, satellite imagery was extracted to the study area and Normalized Difference Vegetation Index (NDVI) is calculated for each image within the assortment of clipped images. Once the NDVI of collections are made, it is band combined to a single raster of .tiff format. NDVI values extracted from the image collection are then organized into a pandas dataframe, which undergoes resampling to a reduced frequency to ensure consistent temporal resolution by addressing any data gaps.

After resampling the NDVI data to a lower frequency, it becomes imperative to partition the dataset into an 80% portion designated for training and a 20% portion for testing. This division

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facilitates the training of the LSTM model on the training subset, followed by its evaluation on the remaining unseen subset to assess its ability to generalize to new observations.

The architecture of the LSTM model which was delineated using Keras was meticulously designed to effectively capture temporal dependencies within the NDVI time series data. Comprising three layers of LSTMs, known for their discern in identifying patterns over time, the model effectively captures the complex temporal relationships present in the dataset. Additionally, a dropout layer is incorporated after the LSTM layers to mitigate overfitting, thereby enhancing the model's robustness and generalization. The final output layer, a dense layer, synthesizes the insights gathered from the LSTM layers to generate predictions that align with the target NDVI values, typically in a single dimension for regression tasks like time series forecasting. To optimize training, the model is constructed with an Adam optimizer, minimizing the Mean Squared Error (MSE) loss function, which encourages the model to generate predictions closely aligned with actual NDVI values. Furthermore, an Early Stopping call back is implemented to prevent overfitting by halting training when the validation loss fails to decrease over a predefined number of epochs, thus enhancing the model's ability to generalize to new data. Upon construction and configuration, the LSTM model undergoes training on the training dataset and validation on the testing dataset. Through this process, the model acquires the ability to translate sequences of NDVI observations into corresponding target values. Subsequently, predictions are generated on the testing dataset, enabling an assessment of the model's performance on unseen data. This rigorous approach ensures the LSTM model is effectively trained, validated, and evaluated for its accuracy in forecasting NDVI values. Moving forward, predictions for NDVI values over the next 7 days will be made, with medians computed and compared against benchmark data from August 2018 to January 2024. By assessing whether predicted NDVI values surpass or align with known values, insights into the crop's health can be inferred, aiding in timely agricultural decision-making. Figure 2 shows the architecture.

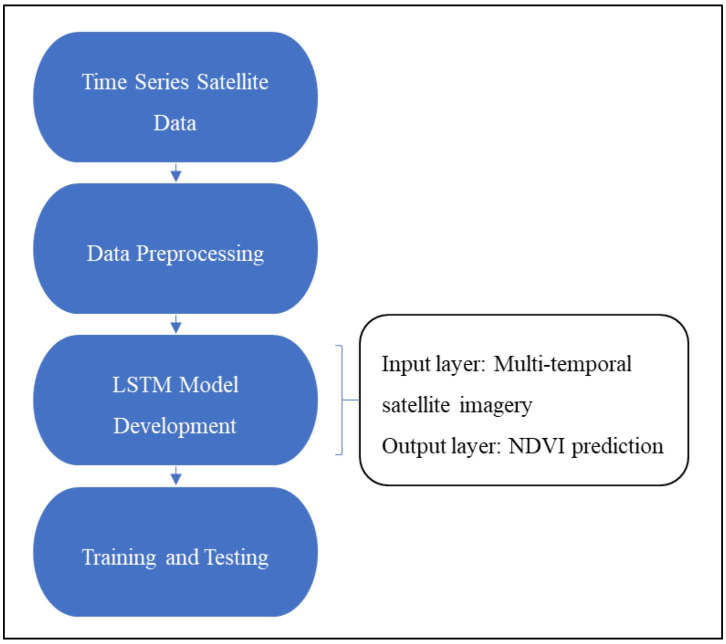

Figure 2. Architecture of LSTM Model

3. RESULTS AND DISCUSSION

The results of this study demonstrate the exceptional capability of the Long Short-Term Memory (LSTM) model in forecasting Normalized Difference Vegetation Index (NDVI) values using Sentinel-2 data. The model achieved remarkable accuracy, as evidenced by the low mean squared error (MSE) of 0.00074, root mean squared error (RMSE) of 0.02722, and

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a high coefficient of determination (R^2) of 0.978. These metrics indicate that the LSTM model is highly effective in capturing the temporal dynamics of NDVI, which is critical for applications in vegetation monitoring, agricultural planning, and environmental management. The high R^2 value (0.978) suggests that the model explains approximately 97.8% of the variance in the NDVI data, which is a strong indication of its predictive power. This performance is consistent with previous studies that have utilized LSTM models for time-series forecasting in remote sensing applications. For instance, [7] and [8] have demonstrated the efficacy of LSTM networks in handling complex temporal dependencies in satellite-derived vegetation indices, further validating our findings. The low MSE and RMSE values also highlight the model's precision in minimizing prediction errors, which is essential for reliable forecasting in dynamic environments such as vegetation monitoring. The visual validation provided in Figure 3 reinforces the model's accuracy, showing a close alignment between predicted and actual NDVI values. The model successfully captures both seasonal trends and short-term fluctuations in vegetation dynamics, which are critical for understanding ecosystem responses to environmental changes. This capability aligns with the findings of [9], who emphasized the importance of capturing temporal patterns in NDVI data for accurate vegetation monitoring. The ability of the LSTM model to replicate these patterns underscores its suitability for applications in precision agriculture and climate change studies.

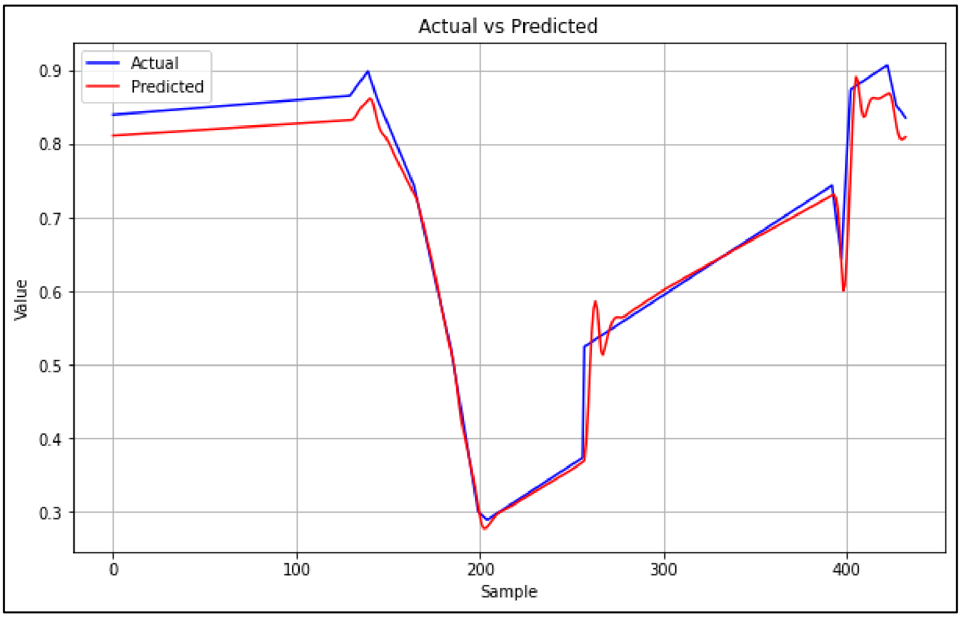

Figure 3. Model Fit (Actual vs Predicted NDVI)

Furthermore, the training and testing loss trends depicted in Figure 4 provide insights into the model's learning process. The consistent decrease in loss values and their convergence around the 125th epoch indicate that the model achieves an optimal balance between learning and generalization. This behavior is characteristic of well-trained deep learning models, as noted by [10], who highlighted the importance of monitoring loss curves to ensure model stability and performance. The convergence of the loss curves in our study suggests that the LSTM model is neither underfitting nor overfitting, which is crucial for its reliability in real-world applications.

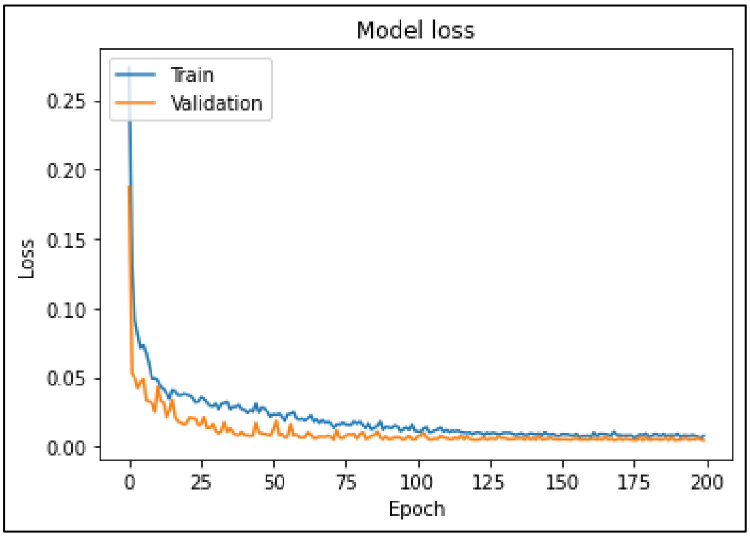

Figure 4. Training and Validation Loss of LSTM Model

The success of the LSTM model in this study can be attributed to its inherent ability to handle long-term dependencies and sequential data, which are fundamental characteristics of NDVI time series. Sentinel-2 data, with its high spatial and temporal resolution, provides a rich dataset for training such models, enabling them to capture subtle changes in vegetation health. This aligns with the findings of [11], who demonstrated the advantages of using high-resolution satellite data for vegetation monitoring and forecasting.

4. CONCLUSION

The study demonstrates the efficiency in forecasting NDVI data, a pivotal indicator in vegetation health using Long Short-Term Memory (LSTM) models. The NDVI data from August 2018 to January 2024, with a benchmark period from August 2019 to March 2020, obtained from sentinel-2 imagery was trained on Google Earth Engine. The model's exceptional performance—evidenced by a Mean Square Error (MSE) of 0.00074, a Root Mean Square Error (RMSE) of 0.02722, and an R-squared value of 0.978—underscores its high predictive accuracy. These findings are significant as they enable proactive decision-making in land management, agriculture, and environmental conservation by comparing predicted NDVI values to optimal vegetation health benchmarks. The study confirms that historical NDVI data can serve as a reliable foundation for assessing current crop conditions and forecasting future vegetation trends. While the results are promising, limitations such as data availability and regional variability suggest the need for further research to refine the model's applicability across diverse environments. Further explorations in the domain by incorporating additional environmental variables and different spatial extents can enhance the robustness of the proposed model. Ultimately, this research highlights the potential of LSTM models as a powerful tool for sustainable and efficient environmental and agricultural practices, offering timely insights for informed interventions.

Conflict-of-interest statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships.

REFERENCES

1. M. Moran, Y. Inoue, and E. Barnes, " *Remote Sensing of Environment*, vol. 61, p. 319, 1997.
2. P. Chavez, C. Yarleque, H. Loayza, V. Mares, P. Hancco, S. Priou, P. Marquez, A. Posadas, P. Zorogastua, J. Flexas, and R. Quiroz, " *Precision Agriculture*, vol. 13, p. 236, 2012.

3. J. W. Rouse Jr., R. H. Haas, J. A. Schell, and D. W. Deering, "Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation," *NASA/GSFC, Type III, Final Report*, Greenbelt, MD, USA, p. 371, 1974.
4. F. Maselli, C. Conese, and L. Petkov, "Use of NOAA-AVHRR NDVI data for environmental monitoring and crop forecasting in the Sahel," *International Journal of Remote Sensing*, vol. 21, no. 18, pp. 3635–3651, 2000.
5. A. Bhandari, A. Kumar, and G. K. Singh, "Feature Extraction using Normalized Difference Vegetation Index (NDVI): A Case Study of Jabalpur City," *Procedia Technology*, vol. 6, pp. 612–621, 2012.
6. M. Dozdar, M. Ahmed, M. Hassan, and R. J. Mstafa, "Title: A Review on Deep Sequential Models for Forecasting Time Series Data,".
7. X. Zhang, Q. Zhang, and G. Zhang, "A Novel Hybrid Model for NDVI Forecasting Using LSTM and SARIMA: A Case Study in the Yellow River Basin, China," *Remote Sensing*, vol. 12, no. 18, p. 2981, 2020.
8. M. Drusch, U. Del Bello, S. Carlier, O. Colin, V. Fernandez, F. Gascon, ... and P. Bargellini, "Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services," *Remote Sensing of Environment*, vol. 120, pp. 25–36, 2012.
9. L. Wang, X. Zhou, X. Zhu, Z. Dong, and W. Guo, "Forecasting Vegetation Dynamics Using LSTM-Based Models: A Case Study in the Mongolian Plateau," *Ecological Informatics*, vol. 61, p. 101214, 2021.
10. S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.