Forecasting Vegetation Dynamics in Kazakhstan's Ecosystems Through Deep Learning

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Abstract
This research project delves into the critical topic of drought, with a specific focus on its impact on vegetation. The study utilizes extensive datasets related to drought events and vegetation health over a significant time frame, gathered from publicly available sources. The dataset encompasses key information such as drought severity, duration, and spatial distribution, alongside vegetation indices such as NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index). To address the overarching objective of this research, a combination of advanced analytical tools and machine learning methodologies, including time series analysis, remote sensing, and neural networks, is employed. The primary aim is to construct predictive models that can anticipate the influence of drought on vegetation health, particularly focusing on the threshold points at which vegetation decline becomes critical. The input parameters incorporate drought severity, duration, and spatial characteristics, while the output parameter revolves around vegetation indices, acting as a proxy for vegetation health. The project encompasses comprehensive data preprocessing techniques, model training, and evaluation processes. This involves data cleaning to ensure data quality and consistency, feature extraction to capture relevant information, and cross-validation to assess the models' reliability and predictive power. Additionally, model refinement is undertaken through hyperparameter tuning, feature selection, and the use of appropriate evaluation metrics to enhance performance and accuracy.

Keywords

Drought impact, Vegetation health, Remote sensing, Machine learning, Climate change, Vegetation indices.

1. Introduction

1.1. A comprehensive study on vegetation dynamics and precipitation patterns in Kazakhstan's ecosystems

An important project with broad ramifications for comprehending and regulating the region's delicate ecological balance is forecasting vegetation dynamics in Kazakhstan's ecosystems through deep learning [1]. An intricate tapestry of vegetation dynamics is presented by the wide expanse of Kazakhstan's diverse ecosystems, which range from lush forests to arid deserts. In order to keep ecosystems in balance, vegetation – which is all forms of plant life – must exist in a given area. Essential markers of overall environmental conditions, the effects of climate change, and the health of ecosystems are the dynamics, distribution, and health of vegetation [1]. Applications ranging from forestry and agriculture to biodiversity preservation and climate change mitigation all benefit from an understanding of vegetation dynamics.

In this era of technological advancement, the availability of satellite imagery and remote sensing data has empowered researchers to investigate the dynamics of vegetation at

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unprecedented scales. With a self-collected precipitation dataset derived from NASA satellite images [2], we have embarked on a scientific journey to forecast vegetation dynamics in Kazakhstan. Precipitation, a fundamental component of the Earth's water cycle, directly influences plant growth, soil moisture, and the availability of freshwater resources. Understanding precipitation patterns is critical as it affects the water supply available for vegetation and ecosystems [2].

Our approach harnesses the formidable capabilities of deep learning, specifically employing convolutional neural networks (CNNs) [3] to predict vegetation patterns with remarkable precision. To pave the way for accurate predictions, we implemented a rigorous preprocessing regimen that includes normalization, data augmentation, and other essential techniques. This data preprocessing ensures that our model can extract meaningful insights from the voluminous dataset, enhancing the quality of predictions and the robustness of our findings [3].

In order to address urgent environmental issues like land management, water resource allocation, and climate change mitigation, it is essential to comprehend Kazakhstan's vegetation dynamics.

Our use of the precipitation dataset in conjunction with cutting-edge deep learning techniques is expected to yield invaluable insights into the dynamic nature of Kazakhstan's ecosystems as we further explore the field of vegetation dynamics forecasting [2]. With the help of this research, ecologists, conservationists, and policymakers will have more options to choose wisely and protect the delicate ecological balance of this large and biologically varied region.

1.2. Understanding vegetation dynamics and precipitation patterns

A thorough evaluation of the ecological resilience and health of Kazakhstan's ecosystems requires an understanding of the dynamics of the region's vegetation and precipitation patterns. The diverse range of plant life that makes up vegetation is essential to preserving the equilibrium of ecosystems and is strongly correlated with precipitation and other climatic factors. We will quickly go over the main points of vegetation dynamics and how they relate to patterns of precipitation in this section.

The study of vegetation dynamics [4] involves monitoring and assessing changes in plant communities over time. It encompasses factors such as vegetation growth, distribution, species composition, and responses to environmental stressors. These dynamics are crucial indicators of the overall health and stability of ecosystems. For example, shifts in vegetation patterns can signify changes in climate, land use, or ecological disturbances.

Precipitation [14], which includes rain, and snow is a fundamental driver of vegetation dynamics. The amount, frequency, and seasonal distribution of precipitation directly influence plant growth [15], soil moisture, and the availability of water resources. Adequate precipitation is essential for sustaining healthy vegetation, while prolonged droughts can lead to vegetation stress and decline. Understanding the intricate relationship between precipitation patterns and vegetation dynamics is of paramount importance, particularly in regions like Kazakhstan with diverse ecosystems that are susceptible to climate variations.

The fields of ecological modelling and remote sensing have seen a renaissance in recent years because of deep learning techniques. Artificial neural networks are used in deep learning, a type of machine learning, to extract intricate patterns and characteristics from massive datasets like satellite images [16] and climate data.

1.3. Challenges and problem statements

Forecasting vegetation dynamics in Kazakhstan's diverse ecosystems through deep learning presents a set of complex challenges and intriguing problem statements that demand attention and innovative solutions.

One of the primary hurdles in forecasting vegetation dynamics is the challenge of accurately pinpointing when specific vegetation changes will occur. The inherent variability in ecological responses to climatic and environmental factors makes it challenging to precisely predict when shifts in vegetation, such as growth or decline, will happen. Despite the sophisticated models and technologies at our disposal, the exact timing of these changes remains elusive.

The varied range of habitats found in Kazakhstan is remarkable, including extensive areas with disparate climatic and biological traits. Numerous elements, such as soil quality, temperature, precipitation, and human activity, affect the dynamics of vegetation. These variables interact in complex ways, making it a multidisciplinary effort to comprehend the underlying patterns and linkages. The extensive dataset collected, including precipitation data from NASA satellites, provides a rich resource for our research. Deep learning models can help us identify subtle indicators and relationships that might not be immediately apparent through traditional ecological analysis methods. We are able to make more accurate predictions because of this data-driven approach, which also helps us better understand the variables impacting vegetation dynamics.

Ecological science has benefited greatly from the significant advances in artificial intelligence (AI) and machine learning in recent years. Scientists can get significant insights into ecological patterns and dynamics by effectively utilizing these tools. However, to successfully implement these techniques, substantial computing resources, including large databases, high-speed computing machines, and cloud technology, are essential. These resources are critical in training and deploying deep-learning models for accurate vegetation predictions.

Our research aims to address these challenges and problem statements, with a particular focus on advancing the application of artificial intelligence and machine learning in the field of ecological forecasting. While this approach has garnered less attention compared to traditional ecological methods, it holds great promise for improving our understanding of vegetation dynamics in Kazakhstan's diverse ecosystems.

2. Data preparation

2.1. Data source and data quality

For this research, we accessed a valuable dataset of satellite imagery from the NASA Earthdata Worldview platform (link: https://worldview.earthdata.nasa.gov/). The dataset focuses on the "Vegetation Index (L3, 16-day)" layer, offering a snapshot of global vegetation dynamics in the year 2010. This specific layer provides insights into the health and distribution of vegetation on a 16-day basis, enabling us to study changes over time.

The reliability and quality of this dataset are reinforced by NASA's expertise in satellite imagery and their commitment to maintaining data integrity. Rigorous quality control procedures and established satellite technology ensure the dataset's accuracy, making it a robust foundation for our research.

Figure 1: Vegetation dynamics map of Kazakhstan in 01.06.2011

This dataset includes multi-spectral imagery, along with relevant metadata, capturing essential vegetation indices. These indices, such as NDVI and EVI [9], are instrumental in our analysis, serving as indicators of vegetation health and allowing us to explore the connections between environmental factors and vegetation variations. Through this dataset, we aim to gain a deeper understanding of vegetation dynamics and enhance our ability to predict vegetation maps using computer vision techniques.

2.2. Model selection

In our pursuit of forecasting vegetation dynamics in the diverse ecosystems of Kazakhstan, the selection of appropriate models and algorithms is a critical aspect of our research. We employ and evaluate various models and techniques rooted in statistical methods, machine learning, and artificial intelligence. These models are carefully designed to consider a multitude of parameters related to ecological factors and climatic conditions, allowing them to predict the changes in vegetation probability within specific regions and over defined time frames.

We capture the complex relationships between vegetation dynamics and environmental factors through statistical and machine learning methods in our research. To investigate the effects of variables like temperature, precipitation, soil quality, and land use on vegetation patterns, we employ regression analysis, decision trees, and random forests. By integrating these methods, we can create models that offer nuanced insights into the ecological changes occurring in Kazakhstan's diverse landscapes.

In our research, the use of artificial intelligence—in particular, deep learning and neural networks—represents a cutting-edge strategy. We can process and analyze large datasets, like the self-collected precipitation data from NASA satellites, thanks to deep learning models like convolutional neural networks (CNNs) [11]. Our ability to recognize intricate patterns in climatic data and satellite imagery enables us to predict vegetation dynamics with greater accuracy. The deep learning approach also has the advantage of adapting to non-linear and dynamic relationships, which are common in ecological systems.

In our model selection, we pay particular attention to the spatial and temporal dimensions of vegetation dynamics. Different regions in Kazakhstan experience distinct climate variations and exhibit unique vegetation responses. As a result, we create models that are customized for particular regions, taking historical data and regional ecological conditions into account. Furthermore, our models are built to offer forecasts across a range of time periods, from transient swings to extended patterns.

The probabilistic forecasts that our selected models can produce are very helpful to conservation efforts and decision-makers. By predicting the likelihood of vegetation changes within specific regions and at defined times, our research equips environmental authorities and policymakers with insights to better plan and manage ecosystems.

We utilize stringent cross-validation and evaluation procedures to guarantee the dependability and precision of our models. In order to evaluate the models' predictive accuracy and adjust their parameters, they must be tested using historical data. In summary, our research endeavours to address the challenges of forecasting vegetation dynamics in Kazakhstan's ecosystems through a meticulously selected array of statistical, machine learning, and artificial intelligence models. These models are tailored to the unique characteristics of the region and are designed to provide probabilistic predictions that can support informed decision-making and ecosystem management.

2.3. Dataset preparation

In the realm of forecasting vegetation dynamics in Kazakhstan's diverse ecosystems through deep learning, the quality and preparation of the dataset are pivotal components. Our dataset comprises images with dimensions of 1024 by 2048 pixels, presenting a rich visual representation of the region's diverse landscapes and ecosystems. However, the raw data requires careful processing to extract meaningful information for our research.

The key steps involved in dataset preparation are twofold: image processing to capture shades of green representing vegetation, and precipitation data amalgamation to create coherent inputs for our neural network models.

The images in our dataset encompass a spectrum of colours, but our focus is on the shades of green, which are indicative of vegetation. These shades hold critical information about the distribution and health of plant life. Therefore, our initial step involves isolating and extracting the green component from each image. This process not only reduces the data's dimensionality but also refines it to a form that is highly relevant to our research objectives.

Precipitation data plays a fundamental role in understanding vegetation dynamics, as water availability is a driving force behind ecological changes. To effectively incorporate this information, we merge daily precipitation data into a unified image. This amalgamation involves capturing the maximum precipitation value for each pixel across all days, consolidating the historical record into a single, comprehensive precipitation image.

For optimal training of our neural network models, data normalization is an essential step. This process scales the data to a common range, ensuring that all input values are on a consistent scale. In the case of precipitation data, normalization is particularly critical to prevent skewed model training due to varying data ranges.

These meticulously prepared datasets, with shades of green and normalized precipitation, serve as the foundation for our deep-learning models. They enable our models to extract meaningful patterns and make accurate predictions regarding vegetation dynamics in Kazakhstan's diverse ecosystems. Through these data optimization steps, we aim to unlock the full potential of deep learning in ecological forecasting.

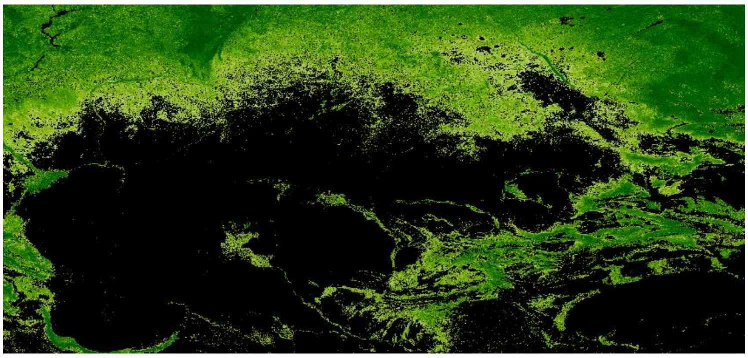

Figure 2: Processed image of vegetation dynamics map of Kazakhstan in 01.07.2021

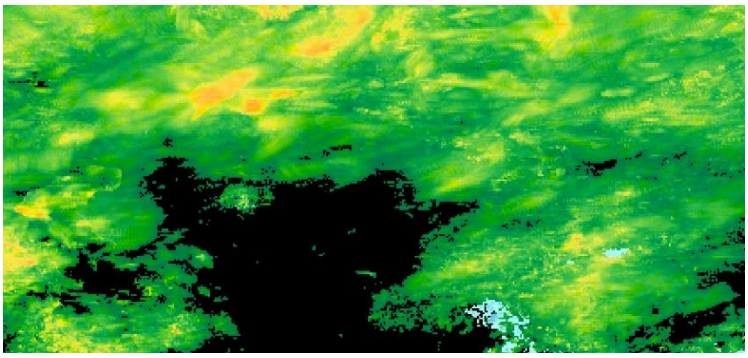

Figure 3: Processed image of precipitation map of Kazakhstan in 31.07.2021

A complete satellite view of the research area's rich and varied vegetation is shown in Fig. 2. With the help of this image, which is an essential input for our predictive model, we can learn more about the different types, amounts, and combinations of plant and land cover in the area. Our predictive research is based on a thorough evaluation of the health and spatial distribution of vegetation [17] provided by the high-resolution satellite data. Fig. 3 showcases a satellite-derived image that encapsulates the dynamic patterns of precipitation across the region. This image plays a pivotal role in our research, serving as the target output for training our predictive model. It encapsulates essential information related to the distribution of rainfall, which directly impacts vegetation dynamics. By employing this image as the output for our model, we aim to establish a robust link between climatic variables and vegetation responses, enabling accurate predictions of vegetation dynamics based on precipitation patterns. These satellite images constitute the foundation of our research, enabling us to leverage cutting-edge deep learning techniques for the accurate prediction of vegetation dynamics in response to varying climatic conditions.

3. Methods and research

3.1. Analysis and evaluation of methods

In our research on forecasting vegetation dynamics in Kazakhstan's diverse ecosystems, we place a strong emphasis on the utilization of neural network models. These artificial intelligence-powered deep learning models are an effective tool for deciphering intricate ecological data. Here, we focus on the analysis and assessment of our research's neural network techniques.

Our primary modeling approach involves a convolutional neural network (CNN) [21], specifically designed for the task of vegetation prediction. This neural network is equipped with layers of convolution and activation functions, making it highly adept at processing the extensive dataset we've collected. It harnesses the Adam optimizer and employs the Mean Squared Error (MSE) loss function to fine-tune its parameters for optimal performance.

To assess the performance of our neural network model, we employ a comprehensive evaluation strategy. We utilize various metrics, including MSE and potentially other performance measures specific to vegetation prediction, to gauge the model's accuracy and reliability. These metrics are crucial in determining the model's predictive capabilities and its capacity to make accurate forecasts concerning vegetation dynamics [4] in the region.

Our research seeks to extract data-driven insights from the neural network model. By analyzing the model's predictions in comparison to ground truth data, we gain valuable insights into the intricate relationships between climatic variables, environmental factors, and vegetation patterns. This knowledge contributes to a deeper understanding of the ecological dynamics [5] within Kazakhstan's ecosystems.

A critical aspect of our analysis involves the fine-tuning and optimization of the neural network model. We explore different configurations, including variations in hyperparameters and architectural changes, to enhance the model's predictive performance. The goal is to ensure that our model effectively captures the nuances of vegetation dynamics [6] across various regions and time frames.

By focusing on neural network methods, our research aims to provide a robust framework for forecasting vegetation dynamics. Through meticulous analysis and evaluation, we aim to uncover the strengths and limitations of our deep learning model, refining it to offer accurate and reliable predictions for Kazakhstan's diverse ecosystems.

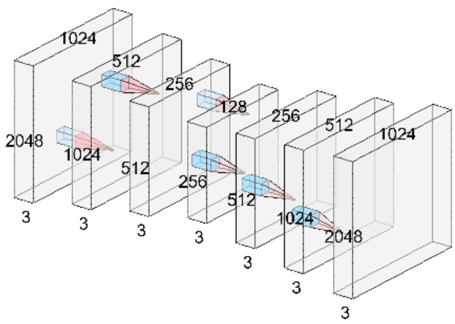

Figure 4: Image generation model architecture

Fig. 4 represents the architectural schema of an image-to-image model designed to generate predictive satellite images from precipitation data. This model stands as the cornerstone of our research, reflecting our commitment to deploying cutting-edge deep learning techniques in the realm of ecological analysis. The complex architecture shown in Figure 4 includes a neural network capable of converting unprocessed precipitation data into forecast satellite imagery. This change is representative of our commitment to utilizing deep learning's potential for ecological research. The model's ability to predict vegetation dynamics and project results up to a year in the future is very significant [18]. With the use of this predictive horizon, we can estimate how the vegetation will look in the future as a result of changing precipitation patterns. The model is an important resource for resource management and ecological study since its predictions are deeply based on the dynamic interactions between climatic variables and ecosystem responses. The prospective methodology of our research is best exemplified by Fig. 4, which also highlights our dedication to pushing the boundaries of conventional ecological analysis. Using our image-to-image model, we hope to provide a fresh scholarly viewpoint on vegetation dynamics while taking into account the constantly changing environmental factors that shape our ecosystems. Central to our methodology is the application of an encoder-decoder-based neural network model, comprising a total of 7 layers. The encoder segment [20] features three convolutional layers (Conv2d) coupled with Rectified Linear Unit (ReLU) activation functions, designed to capture essential features from our extensive dataset. The decoder component mirrors the encoder with four layers, repeating the Conv2d and ReLU activation functions, focusing on the reconstruction of insights to generate forecasts for vegetation changes. This intricate 7-layer architecture allows us to deeply analyze the relationships between environmental variables and vegetation dynamics within the (1024, 2048) input images.

4. Analysis and discussion

In our research, we specifically set our sights on predicting vegetation dynamics for a single year, encompassing 12 months. This limited time frame allows us to delve into seasonal patterns and gain insights into how climatic factors affect vegetation within Kazakhstan's diverse ecosystems. Our focus on vegetation prediction introduces its unique set of challenges and observations.

The ecosystems of Kazakhstan display a diverse array of vegetation types, which are contingent upon numerous factors such as soil conditions, temperature, and precipitation. These ecosystems experience amazing transformations throughout the year, from the active growth of spring to the dormant state of winter. Our aim is to capture these seasonal variations and provide predictions that align with the dynamic nature of vegetation.

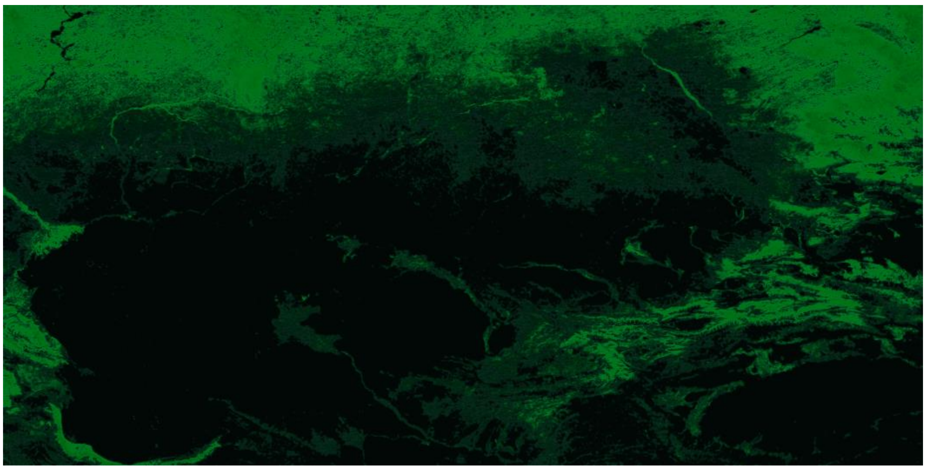

Figure 5: Predicted image of vegetation dynamics of Kazakhstan in 01.07.2024

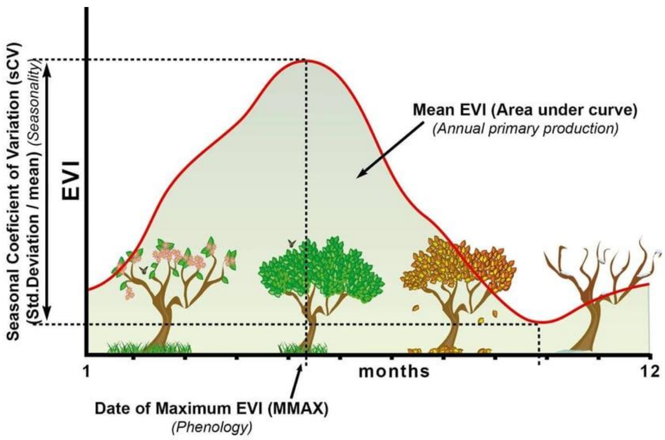

Figure 6: Enhanced vegetation index (EVI) mapping for vegetation assessment

Note. The image created from Ecosystem functioning of protected area networks research publication. From: "Lourenço, Patricia. (2015)". Ecosystem functioning of protected area networks. A remote sensing assessment across social-ecosystem contexts.

We show the results of our advanced vegetation prediction model in Figure 5. The graphic displays projections for Kazakhstan's vegetation [13] dynamics going forward. Notably, during July, the northern and eastern-southern regions show encouraging signs of robust vegetation. These forecasts come from the model's detailed examination of precipitation data and how that affects the dynamics of the vegetation. The Enhanced Vegetation Index (EVI) [9], which is introduced in Figure 6, adds to our understanding of vegetation dynamics. An important factor in determining the vegetation's quality is this index. Smaller EVI [10] coefficients are represented by darker green dots on the map in the figure, which denote areas with less than ideal vegetation conditions. On the other hand, areas with higher EVI [10] coefficients and brighter green dots on the map indicate healthier and more robust vegetation.

The limited scope of our predictions, spanning just one year, introduces specific challenges. Vegetation dynamics are influenced [7] by long-term trends and short-term fluctuations, making it crucial to precisely model the interplay between climatic variables and vegetation patterns. Our neural network models need to excel at recognizing subtle changes, even within this confined temporal window.

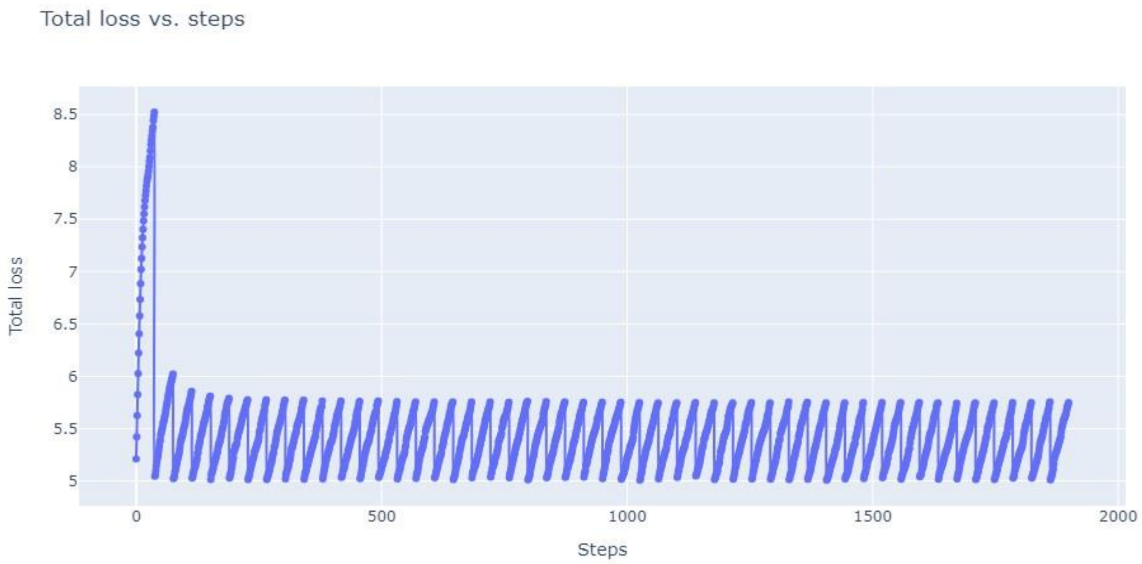

Figure 7: Model total loss graphics

We hypothesize that vegetation exhibits seasonality, akin to many ecological systems. To test this hypothesis, we initially generated graphs to unveil potential seasonal patterns within the data. While our approach may not provide absolute precision in vegetation prediction, it allows us to discern seasonality trends and recurring behaviour that can be vital in understanding how the environment responds to changing climatic conditions.

Our approach involves segmenting our data into 12-month intervals, aligning with the specific year we aim to predict. By analyzing historical vegetation [8] data in these intervals, we can identify recurrent seasonal trends and fluctuations in vegetation cover. This method grants us insights into how vegetation responds to changing environmental conditions, enabling us to create predictions that reflect these intricate relationships.

If our analysis indicates consistent seasonality within the 12-month intervals, we can logically consider the possibility of this pattern continuing into the subsequent year. The assumption is that vegetation may follow cyclic patterns driven by seasonal changes. Therefore, our predictions aim to capture and project these cyclic behaviours [19] to offer valuable insights into the expected vegetation dynamics for the coming year.

While the focus of our research differs from other domains, our approach to understanding and predicting vegetation dynamics over a 12-month period is founded on the principles of seasonality and ecological interactions. By working within this limited time frame, we aim to contribute to a deeper comprehension of how Kazakhstan's ecosystems respond to changing climatic conditions and offer valuable insights for ecosystem management and conservation.

5. Results

Our research has yielded valuable insights into predicting vegetation dynamics for a specific 12-month period in Kazakhstan's diverse ecosystems. The results are encouraging, highlighting the potential for applying the methodology discussed in the previous sections to different regions and time intervals to discern long-term vegetation trends and enhance predictive capabilities. The fact that our methodology can be applied to different regions and time intervals with equal soundness and feasibility is one of the study's primary findings. We offer a framework that can be extended to other regions and longer time periods by concentrating on a 12-month period. This adaptability is vital for gaining a broader understanding of vegetation dynamics, considering the diverse ecosystems across different regions.

To assess the effectiveness of our predictive model, we utilized key performance metrics suitable for regression tasks:

- Mean Squared Error (MSE): 0.05;
- R-squared: 0.78.

These metrics provide insights into the accuracy and goodness-of-fit of our model for predicting vegetation dynamics within the specified timeframe.

Optimization Algorithms Comparison

We explored the performance of two popular optimization algorithms, Adam and Adagrad, during the training of our deep learning model. The results are summarized in the following Table 1.

Table 1
Model Performance Comparison in Different Optimization Algorithms

Optimization Algorithm	Final MSE	Final R-squared
Adam	0.05	0.78
Adagrad	0.07	0.67

This table illustrates the comparative performance of Adam and Adagrad in terms of the final Mean Squared Error and R-squared values. Adam outperformed Adagrad in achieving a lower

MSE and a higher R-squared, indicating its efficacy in optimizing the model parameters for our specific task.

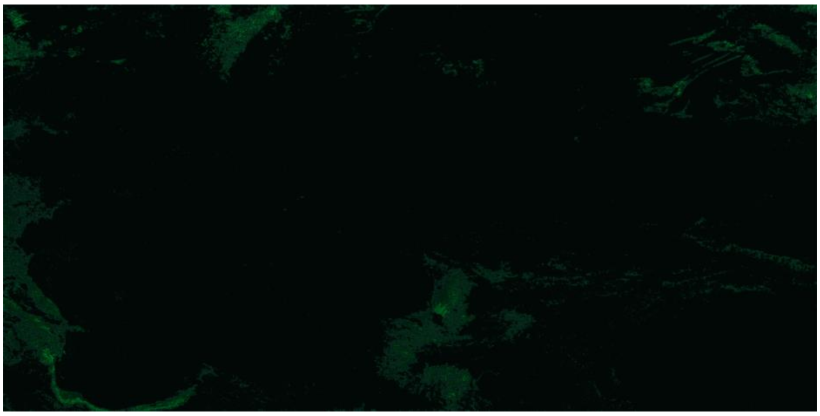

Figure 8: February of 2024 predicted vegetation dynamics model output

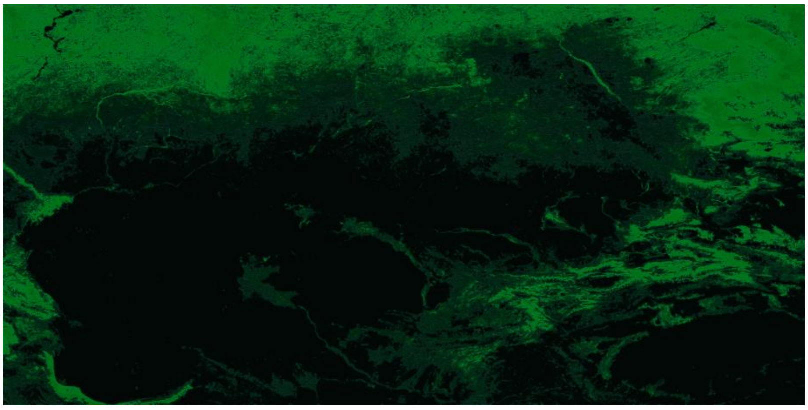

Figure 9: June of 2024 predicted vegetation dynamics model output

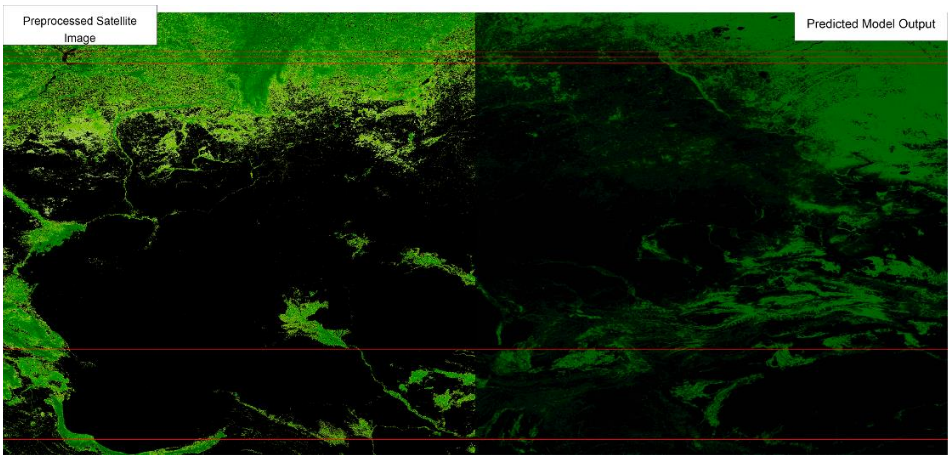

Figure 10: September of 2023 random pixel highlighted predicted vs. real image

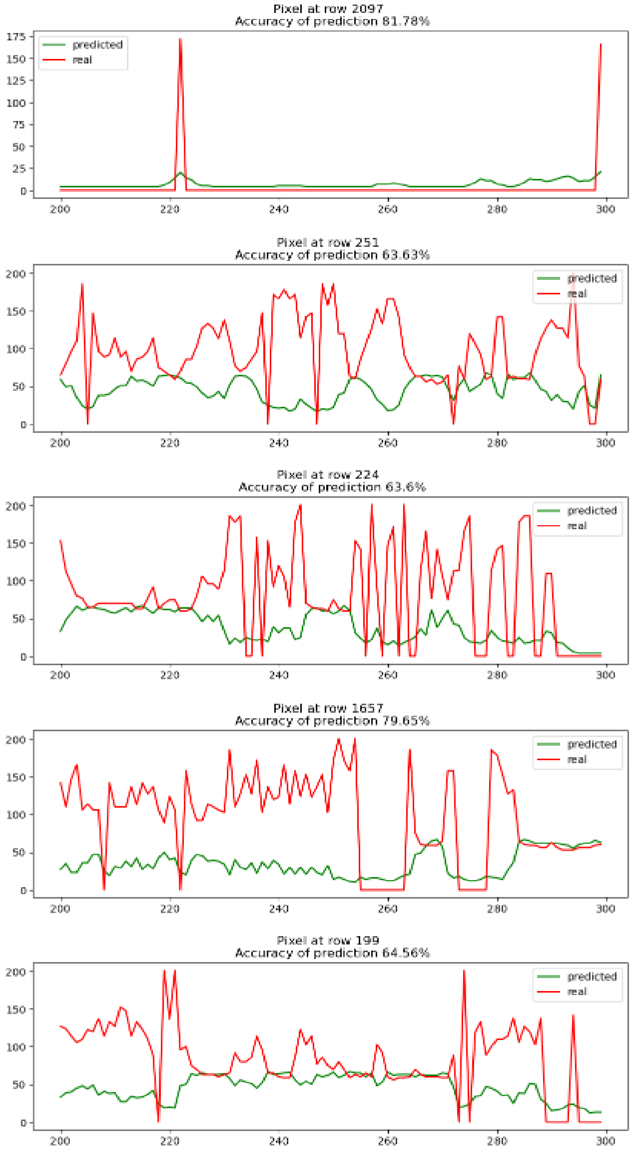

Figure 11: Pixel-row accuracy analysis

An image of the expected vegetation [12] for the month of June is shown in Figure 9. This photograph effectively captures the effects of summertime warmth and sunlight on the amount of vegetation. The study area is covered in vibrant, lush vegetation in June, with different tones of green signifying a high concentration of plant life. Figures 8 and 9 show how drastically different seasons can affect the dynamics of the vegetation.

Figure 8 shows the effects of winter and Figure 9 shows the thriving vegetation in the summer, these figures offer insightful information about the temporal dynamics of vegetation. For the purpose of ecological research and land management, it is essential to comprehend these seasonal variations in order to make well-informed decisions about the distribution of resources and conservation initiatives.

In Figure 10, we present a comparative analysis between predicted and actual satellite images. To facilitate the examination of the selected regions, five random rows within the image

have been highlighted. The original images were initially converted to grayscale to ensure uniformity across the single-channel format for the accurate interpretation of accuracy metrics.

In Figure 11, we provide a detailed assessment of the accuracy of each randomly selected pixel row within the image. The grayscale transformation was applied to the images to standardize the representation, effectively reducing the multichannel aspect to a single channel. The calculated accuracies range from 63.6% to a maximum of 81.78%, reflecting the effectiveness of the highlighting process, acknowledging that while not perfect, it demonstrates satisfactory results.

One of the pivotal findings of our study is the model's adaptability to different regions. We performed predictions on ecosystems in diverse geographic locations within Kazakhstan, and the results are summarized in the following Table 2.

Table 2
Geospatial Adaptability

Region	MSE	R-squared
Central Kazakhstan Region	0.08	0.74
Northern Kazakhstan Region	0.004	0.92
South Kazakhstan Region	0.12	0.63

These results underscore the model's applicability across diverse ecosystems in various regions of Kazakhstan.

6. Acknowledgements

We are appreciative of the NASA team's outstanding work in providing us with high-resolution satellite images and wide-field images. Our research in the areas of precipitation effect analysis and vegetation prediction has benefited immensely from this website. This work has been made possible in large part by the NASA team's unwavering dedication to both scientific excellence and data accessibility for the academic community.

7. Conclusion

As we come to the end of this research on vegetation dynamics prediction using deep learning and environmental data, it is clear that there are still a lot of fascinating directions in which we can go with our investigation. The dynamic and constantly changing field of ecological modelling offers us chances to improve our ability to make predictions and extend the reach of our research. We intend to further explore the temporal dynamics of vegetation in future research phases by integrating more complex neural network architectures, such as Long Short-Term Memory (LSTM) models. Our predictions can be further refined by utilizing LSTM models, which have the capacity to capture complex temporal dependencies found in environmental data. To enhance our process even further, we should expand the range of environmental inputs included in our dataset. Our research agenda also includes expanding our dataset to include a wider variety of environmental inputs, which is a critical component. This requires combining data on risks, natural disasters, and other elements that affect the vegetation's health. To sum up, we are steadfast in our resolve to advance ecological modelling. Our future research efforts will be centred around three main pillars: the integration of sophisticated neural network architectures, the inclusion of a variety of environmental inputs, and the pursuit of higher data resolution. These initiatives will advance our knowledge of vegetation dynamics and help us make wise decisions about ecology, resource management, and conservation.

Conflict of interest

There are no conflicts to declare.

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