Scientific Papers. Series E. Land Reclamation, Earth Observation & Surveying, Environmental Engineering. Vol. XV, 2026
Print ISSN 2285-6064, CD-ROM ISSN 2285-6072, Online ISSN 2393-5138, ISSN-L 2285-6064

DEFORESTATION PREDICTIONS IN NORTHERN ROMANIA USING LONG SHORT-TERM MEMORY NEURAL NETWORKS

Adina NITULESCU

Polytechnic University of Timisoara, 300006, Timisoara, Romania

Corresponding author email: adina.nitulescu@upt.ro

Abstract

Forests are among Earth's most important ecosystems, but unfortunately are vanishing at alarming rates. Thus, deforestation is a global challenge with serious impacts. This paper utilizes Google Earth Engine Landsat data, together with climatic and land-cover data in order to predict the annual deforestation rate in Suceava County. This is being accomplished by using deep learning techniques, more precisely by using Long Short-Term Memory Neural Networks in order to forecast the land changes. These offer distinct advantages in handling time-series data with long-term dependencies, thus making them particularly suitable for tracking changes in vegetation over time. The results have shown an average prediction of 0.45% tree cover loss every year for the next 10 years timeframe. Deforestation studies in Romania have largely focused on spatial analysis but predictive temporal modelling using LSTM remained underexplored. By leveraging the collected data, the paper demonstrates how deep learning techniques can enhance the monitoring and forecasting of forest loss, supporting more sustainable forest management and policy-making. Integrating such approaches could pave the way to anticipating risk and protecting high risk zones before deforestation occurs.

Key words*: climate protection, deep learning, deforestation, predictions.*

INTRODUCTION

An important portion of the EU's biodiversity value forests lies in Romania, but unfortunately this wealth is not being protected enough. Romanian forests occupy around 6.5 million hectares, which translates to approximately 29% of the national territory (Romanian Ministry of Environment, Waters and Forests, 2023). Nowadays, thousands of hectares of forests have been logged and thus, it has emerged as a major environmental concern over the past three decades. Their symbolic value is as important as their ecological and economical one. It is being believed that up until today, illegal logging has cost Romania more than 5.7 billion dollars since the fall of the communism (Lawrence, 2015). One prime example is Suceava County in North-Eastern Romania, which has experienced significant tree-cover loss in the last few decades and which exhibits one of the highest levels of forest loss in Romania (Global Forest Watch, 2025). Yet there are no widely published, formal predictive models specifically for this county deforestation rates in the next 5-20 years available in popular sources. Using deep learning models, Suceava County can be modeled as a high-risk deforestation region, with predictions strongly influenced by past logging intensity, accessibility and climate stress.

Traditional deforestation monitoring methods rely heavily on satellite observation and manual interpretation, which can be time-consuming and less effective for early detection. Recent advances in machine learning, particularly Long Short-Term Memory (LSTM) neural networks, have made it possible to model and predict temporal patterns in environmental data. This study explores how LSTM-based models can be applied to Romanian forest data to predict future deforestation trends. As the drivers of deforestation are usually non-linear and heterogenous, neural networks might help overcome these challenges as they are very good at capturing non-linear functional forms and heterogeneity.

Romania's forests are among the most extensive and biologically diverse in Europe (European Environment Agency, 2024). Figure 1 presents an overview of the current deforestation status in all the EU countries. However, deforestation is not a problem for these countries as overall, Europe is experiencing a net reforestation.

Land-use change in Romania, particularly deforestation accelerated in the past few

decades. In Eastern Europe, land cover and use changes are a consequence of the combined conflict of economy and nature (Gurung et al., 2009). In order to analyze this and look at potential trends, spatially explicit land-use changes must be scale sensitive (Veldkamp et al., 2001; Lausch et al., 2015). Even though these forests are recognized for their exceptional diversity and vital roles in carbon storage, biodiversity conservation and sustainable resource management, the predictions for deforestation are alarming, with a significant amount of natural forest loss and a requirement for reforms to combat the underlying issue (Bohateret, 2012). This is being combined with a degradation of the land, as a result of irrational use of land resources, the abandon or even destruction of improvement systems as well as low fertization of agricultural land (Bălteanu & Popovici, 2010).

Thus, deforestation represents a critical environmental issue in Romania which needs rapid intervention and closer monitoring practices.

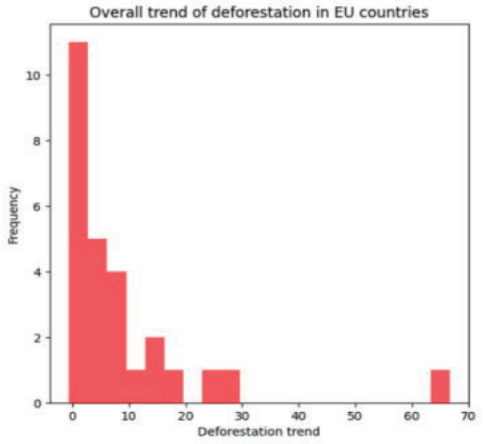


Figure 1. Overall trend of deforestation in EU

The use of AI's predictive power in deforestation forecasting represents a hot topic worldwide. This artificial intelligence enabled tools enable authorities to intervene before forest cover loss happens, providing a useful and reliable tool of real time monitoring and analysis. Similar tools have already been used by authorities in 6 countries but plans are already being developed in order to extend the usage of the AI tools to 12 countries by 2027. The Forest Foresight Model, developed by dutch scientists together with partners from Amazon Web Services aims to predict illegal deforestation up to six months before it occurs (WWF, n.d.). Also, artificial intelligence methods are embedded in platforms such as Google Earth Engine, where the satellite images are being analyzed using machine learning approaches, as well on the Global Forest Watch platform which provides real-time alerts of deforestation activities. These examples reinforce the need and importance of incorporating AI-powered systems in order to diminuate world forest loss (Chatrabhuj & Meshram, 2024).

This paper presents a methodological framework for predicting deforestation trends in Romania using Long Short-Term Memory (LSTM) neural networks. By leveraging satellite imagery, climatic variables, and land-cover data, the study demonstrates how deep learning techniques can enhance the monitoring and forecasting of forest loss, supporting more sustainable forest management and policy-making.

MATERIALS AND METHODS

The shift from simply monitoring what's already gone to forecasting what is at risk in the future represented a breakthrough moment. Nowadays, predicting deforestation using machine learning has become a growing field. Previous studies have employed algorithms such as Random Forests, Support Vector Machines, and Convolutional Neural Networks (CNNs) on remote-sensing data. In this paper, a linear regression model has also been employed in order to forecast forest cover tree loss (Figure 2).

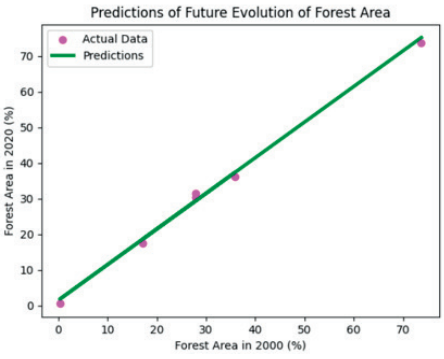


Figure 2. Forest cover loss forecast

Artificial intelligence driven deforestation prediction offers a numerous advantage over traditional monitoring techniques. By allowing less human participation for large-scale prognostic and research, it enables better and more accurate results.

The dataset used in this study includes: Landsat satellite images, collected between 2001 and 2024, vegetation indices, climatic variables, such as temperature, precipitation and soil moisture data as well as land cover data. Images are pre-processed through cloud masking, normalization, and temporal alignment. NDVI time-series are generated for each 1 km² grid cell. The dataset is then divided into training (70%), validation (15%), and test (15%) sets.

Neural networks are computational models of the brain. Artificial neurons are interconnected by edges, forming a neural network. Similar to the brain, the network receives input, internal processes such as activations of the neurons take place and the network yields output. Although these neural networks have a long history of research which dates back to 1943, the number of researchers involved was very small for the first 40 years. It was in 1983 that the funding of neural networks research began being funded in the US.

LSTM networks, a type of Recurrent Neural Network (RNN), offer distinct advantages in handling time-series data with long-term dependencies and are particularly suitable for tracking changes in vegetation over time. Deep learning is a sub-type of machine learning that uses deep neural networks to learn patterns from large amounts of data automatically. For deforestation detection, deep learning models can understand complex image features related to deforestation. Thus, more accurate detection results can be produced as a result (Yu et al., 2020). The collected and analyzed data for Suceava Country, Romania is between 2001 and 2024. Figure 3 presents the percentage of cover tree loss for the above-mentioned period of time.

Romanian forests display considerable variability, covering a broad spectrum of forest types, management approaches, and ecological characteristics, making them representative of wider European forest conditions. Deforestation is fundamentally a human process fuelled by a complex mixture of economic, political, and environmental factors (Malek et al., 2018; Rădulescu et al., 2022).

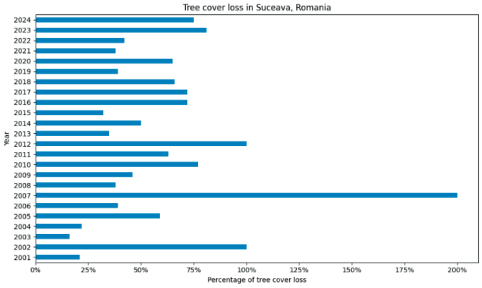


Figure 3. Tree cover loss 2001-2024 in NE Romania

Predicting deforestation is important for targeting interventions and for impact evaluation. Deforestation in general can have serious effects on the quality of life, such as: it worsens air pollution, affects biodiversity, disrupts water cycle and can even increase the risk of a pandemic. Deforestation has been proven to increase the risk of emergence of new diseases, as exemplified for the recent COVID-19 pandemic (Singhal et al., 2024). Predicting the location and timing of future loss is thus incredibly difficult (Cheval et al., 2022). In our paper, we solve this by utilizing Google Earth Engine data, together with climatic and land-cover data in order to provide accurate predictions for the analyzed region. Google Earth Engine is a cloud-based geospatial analysis platform that enables users to visualize, analyze and download satellite images. On top of providing raw imagery, Earth Engine contains several collections of associated data: SR, BAI, EVI, NBR, NDVI, and NDWI at 8-day, 32-day, and annual cadences, allowing for more in-depth analysis (Table 1). Google Earth's capabilities are further enhanced by GEE, which provides on-demand access to a large collection of remote sensing data, allowing for an in-depth and reliable analysis.

The data has been statistically processed and interpreted by building the trend line and setting up the forecast based on simulation models for the period 2025-2035. In Suceava, Romania, the annual deforestation rate has been significant in the past, with a loss of 1.1 kha of natural forest in 2024 only and thus represents a county of major interest.

Table 1. Vegetation indices, formula and description

Index	Formula	Description
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$	Measures vegetation health by comparing NIR reflectance (healthy vegetation) with Red reflectance (chlorophyll absorption). Chosen for its widespread use in assessing vegetation cover and health
Shadow Index (SI)	$SI = (1 - Blue) \times (1 - Green) \times (1 - Red)$	Custom index to detect shadowed areas in forests using visible bands. Selected to differentiate shadows from water and dark surfaces.
Enhanced Vegetation Index (EVI)	$EVI = \frac{(NIR - Red) \times 2.5}{(NIR - 6Red - 7.5Blue + 1)}$	Enhances sensitivity to dense vegetation, reducing soil and atmospheric effects. Effective in monitoring forest canopy health.
Burn Area Index (BAI)	$BAI = \frac{1}{((0.1 - Red)^2 + (0.06 - NIR)^2)}$	Highlights post-fire areas by assessing the spectral difference from charcoal reflectance.
Normalized Burn Ratio (NBR)	$NBR = \frac{NIR - SWIR}{NIR + SWIR}$	A climatic index used to highlight burnt areas in large fire zones.

RESULTS AND DISCUSSIONS

As a summary, from 2001 to 2024, Romania lost around 6.0% of the 2000 tree cover area. Particularly for Suceava County, it meant a total loss of 15% from the 2000 tree cover area. Thus, Suceava County stands out as being one of the most extensively deforested areas in Romania.
The yearly forecast from 2025 to 2035 is approximately 0.45% forest cover loss for each subsequent year. The model predicts a prolongation of the incremental trend in deforestation. It represents a starting point and invites us all to take preventive actions in order to reduce the potential adverse effects deforestation has for the general population.
In this paper, a neural network, specifically the Long Short-Term Memory Neural one has been employed, together with 2001-2024 data in order to predict the deforestation trend in 2025-2035. Long Short-Term Memory Neural Networks have been specifically used for modelling the temporal data of deforestation (Hochreiter & Schmidhuber, 1997).
The LSTM model architecture is presented below in Figure 4.

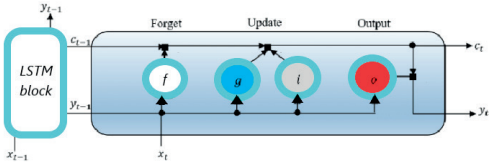


Figure 4. LSTM model architecture

The Long Short-Term Memory (LSTM) architecture is composed of linear units that include a self-recurrent connection with a constant weight of 1.0. This design enables values during the forward pass, as well as gradients during the backward pass, to be retained within the self-recurrent unit and accessed at the appropriate time step. Through this unit multiplier, the output or error from the previous time step is directly propagated to the subsequent time step. As a result, this self-recurrent unit, referred to as the memory cell, is able to store information over long temporal intervals, spanning dozens of time steps.
In our case, we have: one input layer represented by sequential NDVI and climatic data for each pixel, two hidden layers with 64 and 32 units, followed by dropout for regularization, a dense output layer represented by a sigmoid activation predicting the probability of deforestation occurrence in the next year, a binary-entropy loss function and as optimizer, Adam with a learning rate of 0.0001. The model's performance is assessed by using evaluation metrics described in Table 2.

Table 2. Evaluation metrics

Model name	Accuracy	Precision	Recall	AUC
LSTM	0.848169	0.848169	0.848169	0.950000

A variety of metrics can be employed to assess a model's performance, typically based on the counts of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). One widely used evaluation tool is the Receiver Operating Characteristic (ROC) curve that has been plotted in order to evaluate classification performance (Figure 5). The ROC curve is a visual representation of model performance across all thresholds. It is drawn by calculating the true positive rate (TPR) and false positive rate (FPR) at every possible threshold (in practice, at selected intervals), then graphing TPR over FPR.

The trained LSTM model demonstrates high predictive accuracy, particularly in identifying high-risk zones in the Northern Eastern region of Romania and predicting the forest cover loss for the next 10 years timespan.

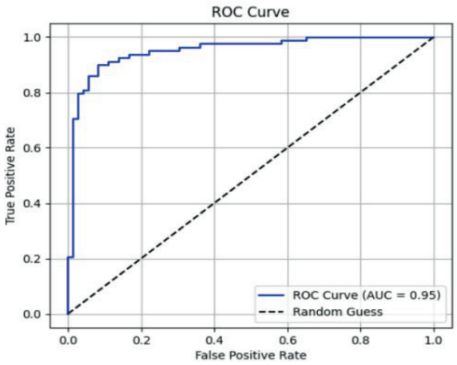


Figure 5. ROC-AUC curve

Areas in Suceava county especially show elevated predicted probabilities of deforestation due to intensive logging and road development. The model's time-series capability allows it to detect early NDVI declines indicative of forest degradation, even before clear-cutting occurs. Compared to the linear regression static model, the LSTM achieved a 10% improvement in F1-score. However, limitations include uneven data quality across regions and the difficulty of distinguishing legal from illegal logging activities. The area under the ROC curve (AUC) represents the capability of the model. The obtained value (0.95) highlights the great power and capability of the model and offers promises. In order to balance the deforestation, several countries bet on reforestation.

Figure 6 presents the differences in forest-cover distribution across European countries in 2000 and 2020, respectively.

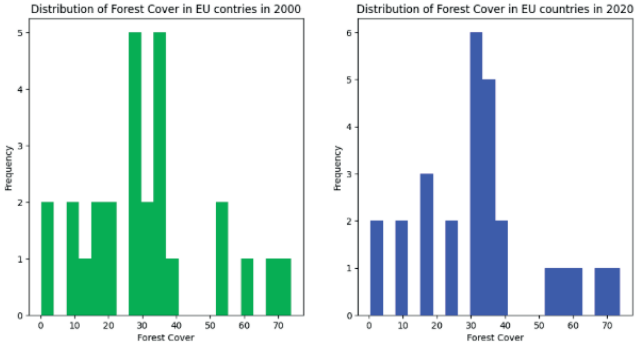


Figure 6. Distribution of Forest Cover in EU countries

Unfortunately, the reforestation trend has been going downwards lately in Romania, as last year (2024) it saw a decrease in forest regeneration efforts, with a total of 25,579 hectares reforested.

CONCLUSIONS

Urgent attention must be paid to the problem of deforestation. However, Romanian forests face big challenges in being efficiently monitored at national scale. Thus, forecasts of deforestation risk could be a vital tool for prevention and protecting nature. Combining data collection, mapping and artificial intelligence approaches, the paper seeked to provide a 10-year overview of forest changes, a case study on the Suceava County in Northern Romania. The findings, exemplified by the percentage and impact of tree cover loss, can guide broader efforts to identify and address dangerous changes in forest cover.

This study demonstrates the feasibility and effectiveness of using LSTM networks for deforestation prediction in Romania. By analyzing temporal trends in vegetation indices and environmental factors, the model provides valuable foresight into forest loss dynamics. Future work should focus on integrating real-time data streams, expanding spatial resolution, and combining deep learning with socio-economic modelling for a more comprehensive understanding of deforestation drivers. These results provide useful insights for a better monitoring system and possible measures to be taken in advance by authorities in order to

prevent cover tree loss. This work lays the foundations of a deforestation prediction model for municipalities of Romania that combines dense neural and LSTM networks. Ultimately, this paper represents a major step forward in harnessing the power of artificial intelligence in forest monitoring and offers a pathway for better global efforts in preserving natural resources in the long-term.

REFERENCES

Bălteanu, D., & Popovici, E. A. (2010). Land use changes and land degradation in post–socialist Romania. *Romanian Journal of Geography, 54*(2), 95–105.

Bohateret, V. M. (2012). Readjusting Romania's forestry policy with a view to the year 2050. *Journal of Settlements and Spatial Planning, 1,* 27–42.

Chatrabhuj, K., & Meshram, K. (2024). Design of an efficient satellite image analysis model for identification of sustainable construction area via ground subsidence monitoring and infrastructure moonitoring operations. *Indian Geotech. J. 54*(3), 1136-1151.

Cheval, S., Bulai, A., & Croitoru, A-E., Dorondel, S., Micu, D., Mihăilă, D., Sfîcă, L., & Tișcovschi, A. (2022). Climate Change Perception in Romania. *Theor. Appl. Clim., 149, 253-272.*

European Environment Agency (EEA). (2024). *Romania: Forest and Biodiversity Report.*

Global Forest Watch. (2025). *Suceava, Romania Deforestation Rates & Statistics,* https://www.globalforestwatch.org/dashboards/country/ROU/36

Gurung, A.B., Bokwa, A., Chelmicki, W., Elbakidze, M., Hirschmugl, M., Hostert, P., Ibisch, P., Kozak, J., Kuemmerle, T., Matei, E., Ostapowicz, K., Pociask-Karteczka, J., Schmidt, L., van der Linden, S., & Zebisch, M. (2009). Global change research in the Carpathian Mountain region. *Mt. Res. Dev.* 29, 282-288.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*. *9*(8), 1735–1780.

Lausch, A., Blaschke, T., Haase, D., Herzog, F., Syrbe, R.-U., Tischendorf, L., & Walz, U. (2015). Understanding and Quantifying Landscape Structure—A Review on Relevant Process Characteristics, Data Models and Landscape Metrics. *Ecol. Model.* 295, 31–41.

Lawrence, P. (2015) Romania acts to save forests from logging spree, *BBC* News, https://www.bbc.com/news/world-europe-33517854,

Malek, Ž., Zumpano, V., & Hussin, H. (2018). Forest management and future changes to ecosystem services in the Romanian Carpathians. *Environment Development and Sustainability*, *20*(3), 1275–1291.

Rădulescu, C. V., Bran, F., Ciuvăț, A. L., Bodislav, D. A., Buzoianu, O. C., Ștefănescu, M., & Burlacu, S. (2022). Decoupling the Economic Development from Resource Consumption: Implications and Challenges in Assessing the Evolution of Forest Area in Romania. *Land. 11(7)*, 1097.

Romanian Ministry of Environment, Waters and Forests. (2023). *National Forest Inventory Report*.

Singhal, V., Jinger, D., Rathore, A.C., Pal, R., Samal, I., Bhoi, T.K., Paramesh, V., Fahad, S., Jaremko, L., Abdelsalam, N.R., & Jaremko, M. (2024) COVID-19, Deforestation, and Green Economy. *Front. For. Glob. Chang.*, 6, 1305779.

Veldkamp, A., Verburg, P. H., Kok, K., de Koning, G. H. J., Priess, J., & Bergsma, A. R. (2001). The need for scale sensitive approaches in spatially explicit land use change modelling. *Environmental Modeling and Assessment, 6*, 111–121.

World Wide Fund for Nature (WWF). (n.d.). *Forest Foresight: technology for early action against deforestation.* https://www.wwf.org.ec/?392413/Forest-Foresight-technology-for-early-action-against-deforestation

Yu, H., Ni, W., Zhang, Z., Sun, G., & Zhang, Z. (2020). Regional forest mapping over mountainous areas in northeast China using newly identified critical temporal features of Sentinel-1 backscattering. *Remote Sens.* 12(9), 1485.