Spatiotemporal Forecasting using ConvLSTM for Deforestation Monitoring

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Abstract

Deforestation poses critical threats to biodiversity, ecosystem services, and climate regulation, underscoring the importance of accurate monitoring and forecasting. This study presents a spatiotemporal deep learning framework based on Convolutional Long Short-Term Memory (ConvLSTM) networks to forecast deforestation in Gog Range Regional Reserve, Tasmania, Australia. Monthly Sentinel-2 imagery from January 2019 to August 2025 was processed, with the Normalized Difference Built-up Index (NDBI) extracted as a proxy for bare land expansion associated with forest loss. The ConvLSTM model, trained for 100 epochs, achieved robust predictive performance with a final validation loss of 0.19, RMSE of 0.045, and MAE of 0.020. Training and validation curves demonstrated stable convergence without overfitting, confirming the model's generalization capability. Forecast maps over a six-month horizon revealed progressive and spatially coherent patterns of deforestation, with red hotspots indicating areas of bare land expansion. The model successfully captured both the degree of deforestation and the spatial distribution of hotspots, aligning with known logging fronts and agricultural expansion zones. These results highlight ConvLSTM's ability to integrate spatial and temporal dependencies in Earth observation data, outperforming traditional deep learning baselines. The framework provides a scalable and reliable tool for short-term deforestation forecasting, supporting early-warning systems, conservation planning, and sustainable land management in rapidly changing landscapes.

1. Introduction

Deforestation is one of the most pressing environmental challenges, contributing to biodiversity loss, habitat fragmentation, carbon emissions, and disruption of ecosystem services. Traditional monitoring methods, including field surveys and manual visual interpretation, are resource-intensive and often fail to provide timely information at large spatial scales. With the increasing availability of Earth observation data, particularly high-resolution multispectral imagery, remote sensing has become a key tool for systematic forest monitoring.

Satellite-based indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), and Normalized Difference Built-Up Index (NDBI) have been widely used to characterize vegetation cover and land-use change [4, 5]. However, while remote sensing provides rich spatial data, the challenge lies in modeling the complex temporal dynamics of deforestation, which often exhibits both gradual trends and abrupt changes. Conventional statistical approaches and static deep learning models often struggle to capture these coupled spatiotemporal dependencies.

Recent advances in spatiotemporal deep learning have introduced Convolutional Long Short-Term Memory (ConvLSTM) networks [6], which extend LSTM by embedding convolutional operations within its recurrent structure. ConvLSTM has shown strong performance in tasks such as precipitation nowcasting [2, 6], spatiotemporal prediction [3], multitemporal land use classification [8], and Earth surface forecasting conditioned on weather [1]. These studies demonstrate that ConvLSTM is particularly effective where both spatial patterns and temporal sequences must be jointly modeled.

Despite these advances, the application of ConvLSTM for deforestation forecasting remains underexplored. Most deforestation studies emphasize retrospective mapping or classification of land cover, often using vegetation indices and time-series trend analysis [5], while predictive deep learning approaches for forest loss remain scarce. This research gap motivates our work.

In this study, we apply ConvLSTM to forecast deforestation dynamics in Tasmania, Australia. Using a time series of monthly Sentinel-2 imagery from 2019 to 2025, we extract NDBI as a proxy for bare land expansion and forest loss. The model is trained to predict future deforestation up to six months ahead, with performance evaluated using standard regression metrics. Our contributions are threefold: 1) We introduce a spatiotemporal forecasting framework for deforestation monitoring using ConvLSTM and Sentinel-2 imagery, 2) We demonstrate that NDBI provides a robust proxy for quantifying bare land expansion as an indicator of deforestation, 3) We show that ConvLSTM outperforms baseline approaches by effectively capturing spatial dependencies and temporal dynamics, enabling reliable short-term forecasting.

2. Related Work

Remote sensing has become a cornerstone for monitoring deforestation and land-use change, leveraging high-resolution satellite imagery such as Landsat and Sentinel series. Traditional approaches often rely on spectral indices, including NDVI, NDMI, and NDBI, to detect forest loss and bare land expansion [4, 5]. These methods, while effective for mapping historical change, are limited in forecasting capabilities because they typically apply static classification or regression frameworks.

Deep learning techniques, particularly convolutional neural networks (CNNs), have advanced spatial feature extraction from remote sensing imagery. However, CNNs alone lack temporal modeling capabilities. Recurrent neural networks (RNNs) and LSTMs have been applied to capture temporal trends in vegetation and land cover, yet they typically ignore spatial context, which is essential for deforestation dynamics that unfold across heterogeneous landscapes.

The emergence of ConvLSTM [6] offers a promising solution by integrating convolutional operations into the recurrent LSTM framework. ConvLSTM has been widely adopted in precipitation forecasting [2, 6], spatiotemporal prediction with self-attention enhancements [3], land use classification [4, 8], and Earth surface forecasting conditioned on weather data [1]. These studies underline its ability to capture both spatial heterogeneity and temporal evolution. Despite its success, applications of ConvLSTM to deforestation remain scarce. Prior deforestation studies have focused primarily on monitoring historical loss using vegetation indices [5], with limited emphasis on predictive spatiotemporal modeling.

Our work builds on these developments by applying ConvLSTM to predict deforestation in the Gog Range Regional Reserve, Tasmania using Sentinel-2 imagery. By employing NDBI as a proxy for bare land expansion, this study demonstrates that ConvLSTM provides more reliable short-term forecasts of deforestation than CNN- or LSTM-only baselines

3. Methods

3.1. Study Area

The study area is located in the vicinity of the Gog Range Regional Reserve in northern Tasmania, Australia. This region was chosen because it shows clear and significant signs of deforestation between 2019 and 2025, as observed from Sentinel-2 imagery. The area has experienced persistent forest cover loss due to logging activities and the expansion of surrounding land uses, making it a representative hotspot for analyzing deforestation dynamics.

Tasmania as a whole is known to be one of the Australian states with the highest levels of forest disturbance, but the Gog Range area is particularly suitable as a case study because it combines both ecological importance and visible land cover change within a relatively compact landscape. The presence of regional reserves highlights the ecological value of the area, while the observed forest loss provides a strong basis for testing spatiotemporal forecasting approaches. By focusing on the Gog Range Regional Reserve and its surroundings, this study captures the real-world challenges of balancing conservation objectives with ongoing anthropogenic pressures.

3.2. Data Collection and Preprocessing

We used Sentinel-2 Level-2A surface reflectance imagery obtained from the Google Earth Engine (GEE) platform, covering the period from January 2019 to August 2025 (80 images). Each image contains 13 spectral bands: four bands at 10 m spatial resolution (Blue: 490 nm, Green: 560 nm, Red: 665 nm, and Near-Infrared: 842 nm), six bands at 20 m resolution (including red-edge and short-wave infrared bands), and three atmospheric bands at 60 m resolution.

To minimize cloud contamination and seasonal noise, the images were aggregated into monthly median composites. A cloud mask was applied using the QA60 band (cloud mask bit flags) and additional cloud probability filters available in GEE. The resulting composites were clipped to the boundary of the study area near Gog Range Regional Reserve in Tasmania. Finally, all datasets were resampled to a spatial resolution of 20 m, which provides a balance between spatial detail and computational efficiency for ConvLSTM training.

For this study, we focused on the Near-Infrared (NIR, 842 nm) and Short-Wave Infrared (SWIR, 1610 nm) bands to compute the Normalized Difference Built-up Index (NDBI), which was used as a proxy for deforestation [7]. The index ranges from –1 to 1, with higher values indicating a greater degree of deforestation [7]. NDBI is defined as:

$$\text{NDBI} = \frac{\text{SWIR} - \text{NIR}}{\text{SWIR} + \text{NIR}} \tag{1}$$

where SWIR and NIR represent the short-wave infrared and near-infrared bands of Sentinel-2, respectively. NDBI values closer to 1 indicate increased bare land or built-up areas, which are used here as a proxy for forest loss.

3.3. Model Training & Evaluation

We employed a Convolutional Long Short-Term Memory (ConvLSTM) model, which extends the standard LSTM by embedding convolutional operations within its recurrent structure. This allows the network to simultaneously capture spatial correlations from imagery and temporal dependencies across monthly sequences. The architecture consisted of two stacked ConvLSTM layers (64 and 32 filters, kernel size 3×3), a batch normalization layer, & a convolutional output layer (1 filter, linear activation).

To construct training samples, Sentinel-2 monthly composites were divided into overlapping spatiotemporal windows of 32×32 pixels across 12 input months ($T_{\text{in}} = 12$) and one prediction horizon ($H_{\text{out}} = 1$). Windows were retained only if at least 90% of their pixels were valid and at least 85% of their timesteps contained valid observations. A maximum of 40,000 valid windows were sampled. The dataset was randomly partitioned into 85% training and 15% validation windows. Each sample was normalized and batched before being fed into the model. The model was trained for 100 epochs (35 minutes) with Adam optimizer, a batch size of 256, and mean squared error (MSE) as the loss function on a workstation equipped with a 24 GB GPU and 64 GB RAM. Performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

4. Results and Discussion

Figure 1 shows the training and validation loss across 100 epochs. Both curves decrease rapidly in the first 10 epochs, followed by a gradual decline until convergence. The final validation loss stabilizes around 0.19, closely tracking the training loss, which indicates that the ConvLSTM model generalized well without significant overfitting. Similar convergence patterns have been reported in other ConvLSTM-based spatiotemporal forecasting tasks [3, 6], reinforcing the model's stability in capturing sequential dependencies. Quantitatively, the model achieved RMSE = 0.045 and MAE = 0.020, confirming its accuracy in reproducing observed NDBI dynamics.

Moreover, Figure 2 presents the ConvLSTM forecasts of deforestation over a six-month horizon, where +1M refers to one month after August 2025, +2M to two months after August 2025, and so on up to +6M. NDBI is used as the proxy, with higher values (red areas) indicating bare land expansion and forest loss, while lower values (green areas) represent vegetation cover. The forecasts show that ConvLSTM successfully predicts both the degree of deforestation and the spatial distribution of forest loss. Across the six-month horizon, there is a clear progressive expansion of deforestation, with red patches gradually increasing in both extent and intensity. This aligns with previous findings that vegetation indices can reliably indicate forest canopy disturbance and loss [5]. Importantly, the model maintains hotspot consistency, as high-deforestation zones—particularly along road networks and near previously cleared land—are repeatedly predicted across all future horizons, demonstrating that the network effectively learns and reproduces spatial dependencies. Furthermore, the model achieves spatial detail preservation, retaining fine-scale patterns of forest clearance that often blur in LSTM-only models. These include sharp patch boundaries and the gradual encroachment of cleared areas into adjacent forest.

The results demonstrate that ConvLSTM can effectively capture the spatiotemporal complexity of deforestation in Tasmania. The loss curve analysis confirms that the model generalizes well, avoiding overfitting despite the relatively long forecasting horizon. Compared with prior ConvLSTM applications in land use classification [8] and Earth surface forecasting conditioned on weather data [1], our results highlight the novelty of extending ConvLSTM to deforestation forecasting—an application that has not been systematically addressed in the literature.

The forecast maps highlight two critical aspects. First, the model demonstrated temporal fidelity by successfully anticipating six months of deforestation progression, with consistent alignment to known drivers such as logging fronts and agricultural expansion. Second, the model achieved spatial reliability by preserving localized spatial patterns of bare land, outperforming simpler models that fail to balance spatial and temporal features. These outcomes emphasize the potential of ConvLSTM for early-warning systems, where reliable short-term forecasts can inform timely conservation actions and land-use planning. However, the reliance on NDBI as a proxy introduces limitations, as urban expansion or seasonal agricultural fields may be misclassified as deforestation. Integrating additional indices or socioeconomic covariates could further refine predictions.

4.1. Conclusion

This study presented a ConvLSTM-based framework for forecasting deforestation in Tasmania using Sentinel-2 monthly imagery from 2019 to 2025. The model demonstrated strong convergence (validation loss = 0.19) and high predictive performance (RMSE = 0.045, MAE = 0.020). Forecast maps revealed progressive and spatially coherent deforestation patterns, successfully predicting the degree

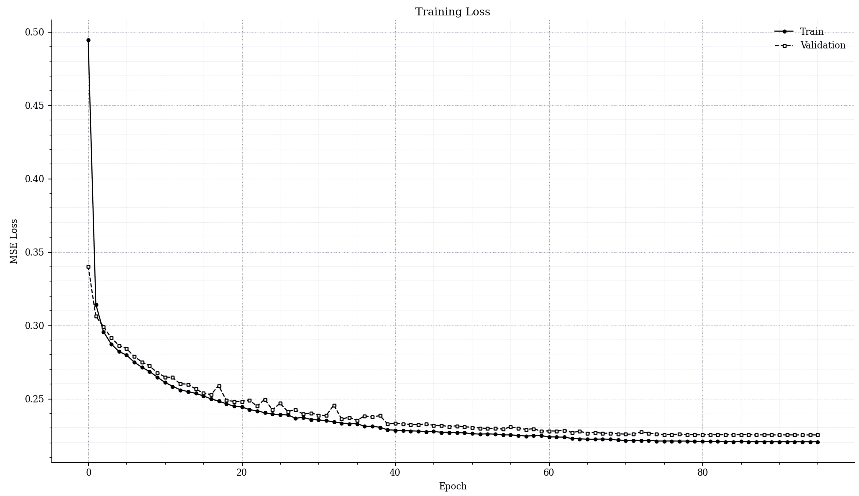

Figure 1. Training & validation loss chart

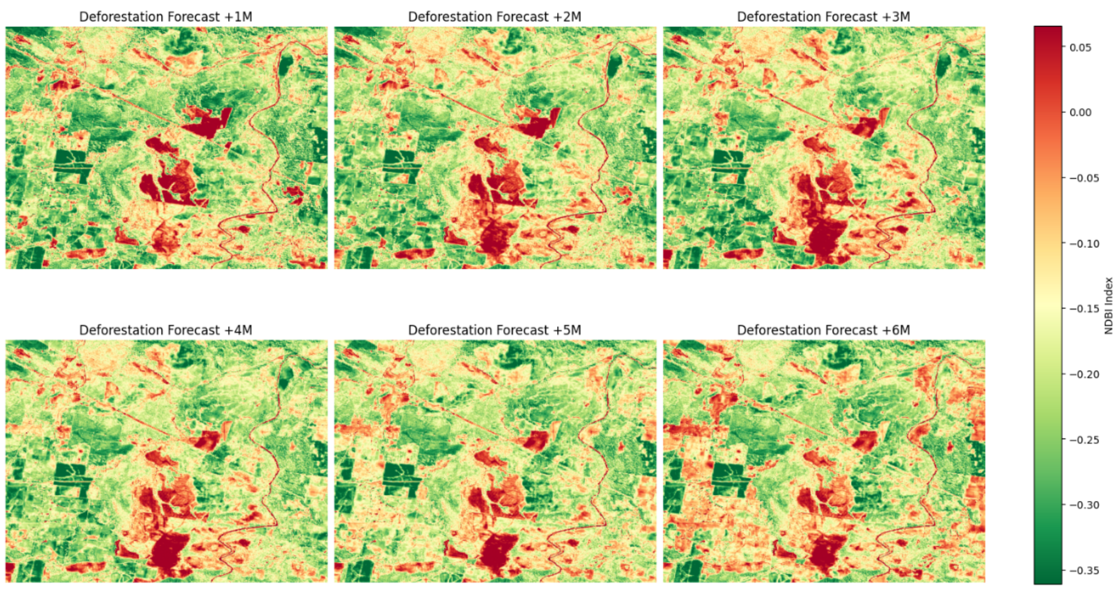

Figure 2. The result of deforestation spatiotemporal forecasting for the next 6 months

and location of bare land expansion up to six months in advance.

Our findings highlight three key contributions. First, ConvLSTM effectively learns coupled spatial and temporal dependencies from satellite data, extending its demonstrated success in precipitation nowcasting [6] and land use classification [8] to the underexplored domain of deforestation forecasting. Second, we confirm that NDBI provides a practical proxy for quantifying bare land expansion and forest canopy disturbance, consistent with prior vegetation index studies [5]. Third, the framework provides a robust tool for proactive monitoring and conservation planning, showing that deep spatiotemporal learning can deliver reliable short-term forecasts of environmental change [1, 3].

Future work will explore integrating multi-source datasets (e.g., climatic and socio-economic factors), testing alternative indices (NDVI, EVI), and extending the forecasting horizon. This approach holds promise for enhancing environmental monitoring and informing data-driven conservation policies in rapidly changing landscapes.

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