

REMOTE-SENSING DATA-DRIVEN CLASSIFICATION OF DEFORESTATION BASED ON DEEP LEARNING IN SARAWAK

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Abstract

This study explores the application of deep learning models for classifying drivers of deforestation in Sarawak, Malaysia, using multi-temporal Landsat imagery and topographic data. The research evaluates multiple deep learning architectures' performance in classifying four major deforestation drivers: plantations, smallholder agriculture, grassland/shrubland conservation and other land use changes. Using transfer learning techniques, models were trained on 632 expertly annotated Indonesian deforestation events and applied to Sarawak's context. Among the tested architectures ResNet-18, EfficientNet-B2, UNet, Vision Transformer and TransResNet, the EfficientNet-B2 model achieved the highest accuracy of 65 on the test dataset. Analysis of 140 forest loss events in Sarawak between January 2017 and December 2018 revealed that plantations as the primary driver (45.7% of cases) followed by other land use changes (39.3%), grassland/shrubland conversion (12.9%) and smallholder agriculture (2.1%). Temporal analysis using four-year-post-deforestation imagery composites (2018-2021 for 2017 events; 2019-2022 for 2018 events) showed significant shifts in deforestation patterns, with plantation-driven deforestation decreasing from 47.1% to 44.3% between 2017 and 2018. The study highlights the potential of transfer learning in developing generalized models for tropical forest regions. However, limitations such as lack of region-specific data and ground truth validation underscore the need for further research to enhance the accuracy and applicability of these models in local contexts.

Keywords: Data science, Deep learning, Remote sensing, Sarawak deforestation, Satellite imagery,.

1. Introduction

Tropical deforestation continues to be a pressing global environmental issue, with far-reaching consequences for climate change, biodiversity, and ecosystem. Malaysia, particularly the state of Sarawak on Borneo, presents a compelling case study in tropical forest management and conservation efforts.

Since gaining independence in 1963, Malaysia has lost approximately 6.3 million hectares of forest cover. However, this trend has not been linear. In 1992, at the Earth Summit in Rio de Janeiro, Malaysia pledged to maintain at least 50% of its land area under forest cover – a commitment it has largely upheld. As of 2020, Malaysia's forest cover stood at 54.8% or 18.1 million hectares. Sarawak, with 7.7 million hectares of forest covering 62% of its land area, accounts for 43% of Malaysia's total forest cover. However, it faces ongoing pressure for deforestation, especially for agricultural expansion. The state is considered the "last frontier" for oil palm plantation development in Malaysia [1].

Studies have found that industrial plantations, particularly oil palm and pulpwood, have been major contributors to forest loss in Borneo. Between 1973 and 2015, approximately 18.7 million hectares of old-growth forest were cleared across Borneo, with industrial plantations expanding by 9.1 million hectares (7.8 million hectares oil palm; 1.3 million hectares pulpwood). The drivers and patterns of deforestation have varied across different regions and time periods. In Malaysian Borneo, 57-60% of deforestation between 1973 and 2015 was associated with rapid conversion to industrial plantations within five years of forest clearance. In contrast, only 15-16% of deforestation in Indonesian Borneo followed this rapid conversion pattern [2]. Remote sensing and geospatial analysis have enabled more precise quantification of forest cover change and identification of deforestation drivers over time [3, 4].

As Malaysia strives to balance economic development with forest conservation commitments, there is a need for comprehensive policies and institutional frameworks to govern land use change and forest management. This is particularly important in states like Sarawak, where complex issues of land rights, agricultural expansion pressures, and conservation priorities intersect [1]. This study aims to advance deforestation monitoring through three specific objectives: (1) evaluate the effectiveness of transfer learning for deforestation classification between Indonesian and Malaysian Borneo contexts, leveraging their geographical proximity and ecological similarities; (2) quantify and compare model performance in classifying four specific deforestation drivers: plantations, smallholder agriculture, grassland/shrubland conversion and other land use changes; and (3) assess temporal changes in deforestation patterns between 2017-2018 using consistent multi-year post-disturbance imagery analysis.

2. Related Work

Remote sensing and geospatial analysis have revolutionized our ability to monitor and understand deforestation patterns and drivers. Several key studies have paved the way for analysing forest cover change using satellite imagery and advanced computational techniques. Hansen et al. [5] developed high-resolution global maps of 21st-century forest cover change using time-series analysis of Landsat images. This groundbreaking work provided annual, 30-meter resolution data on forest loss and gain globally, enabling more detailed analysis of deforestation trends. Building on this forest change

data, Curtis et al. [6] used a decision-tree model to classify drivers of global forest loss into categories like commodity production, shifting agriculture, and forestry.

Focusing on Indonesia, Austin et al. [3] conducted a granular assessment of deforestation drivers annually from 2001-2016. Using visual interpretation of high-resolution imagery, they classified drivers into categories like oil palm plantations, small-scale agriculture, and grassland/shrubland expansion. Their analysis found that oil palm plantations drove almost close to 40% of deforestation nationally but declined in importance after 2009. Gaveau et al. [2] examined four decades of industrial plantation expansion in Borneo, including Sarawak. Using Landsat imagery, they mapped the expansion of industrial plantations (primarily oil palm and pulpwood) and resulting deforestation from 1973-2015. They found that 76% of deforestation in Malaysian Borneo was associated with industrial plantations, compared to just 15-16% in Indonesian Borneo, highlighting the strong link between plantations and forest loss in Malaysian states like Sarawak.

Recent studies have leveraged new satellite data sources and advanced machine learning techniques for more precise mapping of deforestation drivers. Descals et al. [7] used deep learning methods on Sentinel-1 radar and Sentinel-2 optical imagery to map both industrial-scale and smallholder oil palm plantations globally for the year 2019. Their analysis produced high-resolution (10 m) maps distinguishing industrial closed-canopy oil palm, smallholder closed-canopy oil palm, and young oil palm plantations. The availability of radar imagery from satellites like Sentinel-1 has given rise to a new generation of remote sensing studies benefiting from cloud penetration, improved resolution, and high revisiting frequency. Fusion of optical and radar data can help overcome limitations of individual sensors. For example, Poortinga et al. [8] combined Landsat-8, Sentinel-2, and Sentinel-1 data to map oil palm plantations in Myanmar, achieving high accuracy (84-91%) in detecting plantations.

While satellite-based methods provide broad coverage, UAV-based methods have emerged as a complementary approach for detailed local analysis. Phang et al. [9] demonstrated that UAVs can capture high-resolution imagery particularly valuable for complex, heterogeneous landscapes like Sarawak where satellite data alone may miss fine-scale forest changes. The flexibility and resolution of UAVs make them especially effective for validating satellite observations and monitoring small-scale deforestation patterns.

Deep learning approaches are increasingly being applied to remote sensing data for land cover classification tasks. As reviewed by Vali et al. [10], convolutional neural networks and other deep learning architectures have shown promising results for classifying land use and land cover from multispectral and hyperspectral satellite imagery. Apart from deforestation, remote sensing has also been widely applied in other environmental monitoring initiatives including water monitoring [11] and soil erosion [12] etc. These methods can automatically learn relevant features from the data, potentially improving classification accuracy compared to traditional machine learning approaches. For detecting selective logging and forest degradation, which can be more subtle than clear-cutting, Hethcoat et al. [13] demonstrated that a machine learning approach using Landsat data could detect low-intensity selective logging (< 15 m³/ha) in the Brazilian Amazon. Their random forest classifier was able to detect logging soon after harvest with approximately 90% accuracy (with ~20% commission error).

To address challenges like limited training data, researchers have explored various strategies. Chen et al. [14] used a transformer-based architecture to perform change detection between pairs of remote sensing images. The self-attention mechanism in

transformers allowed the model to capture long-range dependencies in the spatial domain. Masolele et al. [15] investigated spatial and temporal deep learning methods for deriving land use following deforestation, finding that models accounting for both spatial and temporal patterns outperformed those using only spatial or temporal information.

Despite these advances, several methodological gaps persist in deforestation driver classification. Current approaches heavily rely on region-specific training data, limiting their applicability across different geographical contexts. While both Indonesian and Malaysian Borneo share similar ecological characteristics, cross-regional validation of classification models remains limited. Additionally, most studies focus on single-time-point classification rather than integrated temporal analysis of land use transitions. This study addresses these limitations through a systematic cross-regional approach within Borneo Island, combining transfer learning with multi-temporal analysis.

3. Methods

The methodology consists of three stages: (1) Data collection and processing, (2) Model architecture selection, (3) Model training and evaluation.

3.1. Data collection and processing

Primary forest loss data was derived from the Hansen et al. Global Forest Change (GFC) dataset (version 1.11) [5] provides annual, 30-meter resolution data on global forest dynamics. The GFC data, defined as stand-replacement disturbance or complete removal of tree cover canopy at the Landsat pixel scale, was spatially constrained to Sarawak's administrative boundaries. A forest cover threshold of 30% for the year 2000 was applied to outline forested areas and contiguous patches of forest loss were aggregated into discrete "events" using an eight-neighbour connectivity rule, allowing for the analysis of cohesive deforestation units [3, 16].

While more recent deforestation events exist, the study period was constrained to 2017-2018 to ensure the availability of complete 4-year post-deforestation imagery composites: 2018-2021 for 2017 events and 2019-2022 for 2018 events. Analysis of events after 2019 would lack the required temporal depth for consistent land use transition tracking.

To characterize post-disturbance land cover trajectories, the study leveraged Landsat 8 Collection 2 Tier 1 Surface Reflectance products [3]. For each identified forest loss event, a time series of Landsat 8 imagery was compiled, spanning four consecutive years following the deforestation event. This temporal window enabled the observation of land cover transitions and vegetation regrowth patterns. The spatial extent for each event was defined as a 5 km x 5 km region centered on the deforestation locus, encompassing approximately 2,500 hectares.

Image selection criteria prioritized minimal cloud contamination, with a maximum cloud cover threshold of 50% implemented during the filtering process [16]. Annual median composite images were generated from all available scenes meeting the cloud cover criteria, mitigating the effects of atmospheric perturbations, and ensuring data continuity. The analysis focused on the visible spectrum bands (Red, Green, and Blue), which were synthesized to create true-colour composites amenable to both visual interpretation and machine learning classification algorithms.

To account for topographic influences on deforestation patterns and subsequent land use decisions, the study incorporated elevation data from the Shuttle Radar Topography Mission (SRTM) [16]. The SRTM dataset, offering near-global coverage at 1 arc-second resolution, was used to derive slope information for each forest loss event. This topographic variable was crucial in understanding land suitability for various anthropogenic activities and was processed to align with the spatial resolution and extent of the Landsat imagery. Examples of pre- and post- forest loss images are shown in Fig. 1.



Fig. 1. Pre-forest loss (left) and post-forest loss (right).

Note: While SRTM data was used for topographic analysis, the images shown here are Landsat 8 true-colour composites to illustrate visible land cover changes. SRTM data was processed separately for slope analysis.

3.2. Model architecture selection

The study built upon and extended the deep learning approach introduced by Ramachandran et al. [16] for deforestation driver classification. This research implemented and compared several deep learning architectures, replicating and expanding on their work. The baseline model employed was a ResNet-18, a deep residual network architecture with 18 layers that has shown strong performance in various computer vision tasks. The study also utilized the EfficientNet-B2 architecture, which proved effective in the original study [16]. The EfficientNet-2 architecture was selected for its proven efficiency in balancing model capacity and accuracy through compound scaling of network dimensions. Unlike traditional models that scale dimensions arbitrarily, EfficientNet-B2 uses a compound coefficient to uniformly scale network width, depth, and resolution, resulting in better accuracy and efficiency trade-offs.

In addition to these convolutional neural network (CNN) models, the research explored other architectures to capture different aspects of the satellite imagery. The UNet architecture, originally designed for biomedical image segmentation, was adapted to the classification task [17]. This fully convolutional network architecture allows for fine-grained spatial information to be preserved throughout the network.

To leverage recent advancements in natural language processing applied to computer vision, a Vision Transformer (ViT) model was implemented. This pure transformer-based model processes the image as a sequence of patches, utilizing self-attention mechanisms to capture global dependencies in the input [18].

Furthermore, the study developed a hybrid model called TransResNet, combining the strengths of CNNs and transformers. This architecture, inspired by the work of Wang et al. [19], uses a ResNet backbone to extract local features through multiple convolutional layers, followed by a transformer encoder with 12 layers and 16 attention heads to model global relationships. The architecture includes a decoder network that up samples features back to the original resolution and a classification

head specifically designed for deforestation driver prediction. This comprehensive approach aims to capture both fine-grained spatial information and long-range dependencies in the satellite imagery. To optimize model performance, extensive hyperparameter tuning was conducted across all architectures. For TransResNet, this included grid search over learning rates (0.0001-0.1), batch sizes (16-32), and weight decay values (0.01-0.1). Additional tuning focused on the number attention heads (8-16) and encoder layers (6-12), with 16 heads and 12 layers providing the best validation performance. To improve the quality of learned representations, contrastive learning techniques were incorporated into the training process following the contrastive learning approach outlined by Chen et al. [20]. Data augmentation strategies including random horizontal flipping, 270-degree rotations, and elastic deformations were applied with the carefully tuned parameters. These augmentations combined with the regularization techniques such as dropout (0.1-0.5) and weight decay improved the models' generalizability by creating diverse views of the same image and reduce overfitting [21].

By replicating and building upon the architectures used in the original study [16], while incorporating additional models and training techniques, this research aimed to comprehensively evaluate the effectiveness of various deep learning approaches for deforestation driver classification.

3.3. Model training and evaluation

The deep learning models' training regime utilized a pre-existing dataset from a comprehensive study on deforestation drivers in Indonesia [3]. This dataset however deprecated from the one used in Ramachandran et al. [16]. Although the original study utilized a larger dataset, only 632 expertly annotated forest loss events were publicly available at the time of this study. These events were categorized into four broad classes of deforestation drivers: Plantation, Smallholder agriculture, Grassland/Shrubland, and Other. While both Indonesian and Sarawak datasets originate from Borneo Island, some regional variations exist. To address these differences, our data preprocessing pipeline mirrored the approach used in the Indonesian study [3], ensuring consistency in spatial resolution, temporal coverage, and feature extraction. This included matching the cloud filtering thresholds, although regional differences in cloud cover patterns may have influenced final accuracy. Despite the lack of ground truth data for Sarawak, the model's validation strategy leveraged the geographical proximity and ecological similarities between the regions, with the Indonesian training data serving as proxy for regional deforestation patterns.

Aforementioned data augmentation was utilized to enhance the dynamism of the models. The models were trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 16 for 20 epochs. Cross-entropy loss was used as classification learning while a supervised contrastive loss was used for representation learning.

To assess the models' performance and transferability to the Sarawak context, an unlabelled dataset was compiled consisting of 140 forest loss events from 2017-2018. The selection of these events was predicated on the availability of a complete four-year Landsat 8 time series following the deforestation event, ensuring consistency in the temporal analysis across all samples. For each event in the test dataset, a comprehensive data package was assembled, including the multi-year Landsat 8 imagery, derived slope information, and precise spatiotemporal coordinates of the forest loss events.

4. Results and Findings

4.1. Model performance on Indonesia test dataset

The performance of the trained models on the Indonesia test dataset is summarized in Table 1. The EfficientNet architecture demonstrated the highest accuracy (0.65), followed by UNet (0.51) and ResNet (0.49). This superior performance can be attributed to EfficientNet-B2's optimized scaling strategy and efficient feature extraction capabilities. The Vision Transformer and TransResNet models showed lower accuracies of 0.48 and 0.46, respectively. The varying performance across models reflects the inherent challenges in cross-regional deforestation classification. Models showing accuracy below 50% (ResNet:49%, Vision Transformer:48%, TransResNet:46%) were particularly affected by limited training data (632 samples) relative to model complexity, class imbalance in the training dataset and different atmospheric conditions between regions affecting image quality. While TransResNet's hybrid approach combining CNN and transformer components showed promise in capturing both local and global features, the additional architectural complexity may have contributed to its lower performance given the limited training data available. Although the transformer models demonstrated an increasing trend of accuracy over each training loop, computational constraints (AMD Ryzen 5 5500U with Radeon Graphics, 2.10 GHz with a 5-hour training time limit per model) hindered the ability to fully explore their ability in deforestation driver classification under intensified configurations and parameters.

Table 1. Model performance on Indonesia test dataset.

Model	Deep Learning		UNet	Transformer	Hybrid Model
	ResNet	EfficientNet		Vision Transformer	TransResNet
Accuracy	0.49	0.65	0.51	0.48	0.46

The achieved accuracy of 65% on the Indonesian test dataset is comparable to similar cross-regional studies, being only 7% lower than the 72% accuracy reported in the original Indonesian study [16]. This modest reduction in performance can be attributed to several factors, including difference in cloud filtering procedure and regional landscape variations. While the accuracy might seem moderate, it represents a significant achievement in cross-regional transfer learning especially considering the complexity of distinguishing between similar land use transitions in tropical forests. The model's performance could be improved through enhanced cloud filtering algorithms, incorporation of additional spectral bands and region-specific fine-tuning when the ground truth data becomes available.

4.2. Model prediction on Sarawak dataset

When applied to the Sarawak test dataset (140 samples from 2017-2018), the best-performing model (EfficientNet) produced the distribution of predicted labels shown in Fig. 2. Plantation emerges as the predominant driver, accounting for 64 instances, followed by Other with 55 instances. Grassland shrubland is predicted in 18 cases, while Smallholder agriculture is observed in only 3 instances. This distribution indicates a significant prevalence of large-scale agricultural activities, particularly plantations, as the primary drivers of deforestation in the region. The substantial number of "Other" predictions may suggest either a diversity of less frequent drivers

or potential limitations in the classification model's ability to categorize certain deforestation events definitively.

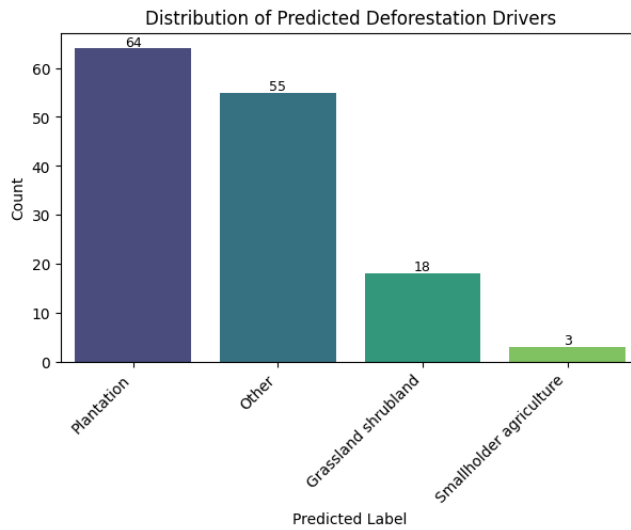


Fig. 2. Distribution of predicted deforestation drivers.

Figure 3 illustrates the temporal change in predicted deforestation drivers from 2017 to 2018. A notable decrease in Plantation-driven deforestation is observed, from 47.1% to 44.3%. Conversely, the ‘Other’ category exhibits a marked increase from 35.7% to 42.9%. Grassland shrubland deforestation demonstrates a decrease from 15.7% to 10.0%, while Smallholder agriculture shows a modest increase from 1.4% to 2.9%. These shifts may be indicative of evolving land use policies, economic factors influencing plantation expansion, or the implementation of forest protection measures targeting large-scale deforestation activities. Further investigation into the underlying causes of these changes is warranted to fully understand the dynamics at play.

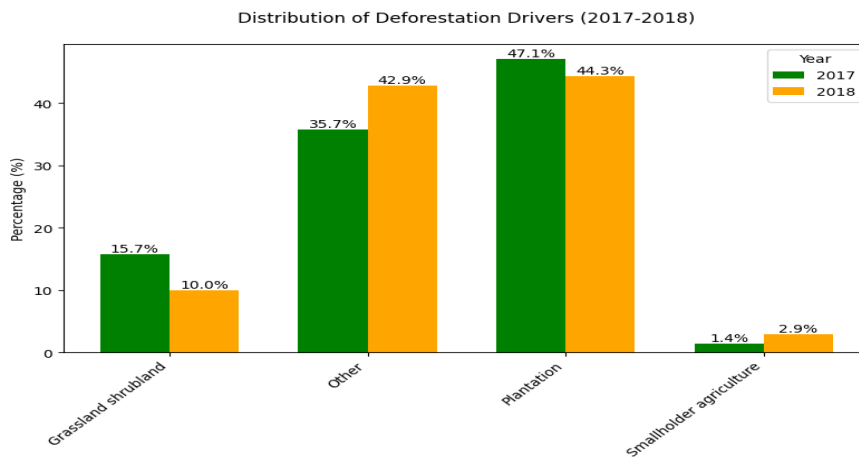


Fig. 3. Percentage change in predicted drivers from 2017 to 2018.

The spatial distribution map of predicted deforestation drivers across Sarawak in Fig. 4. reveals distinct patterns. Plantation and Other drivers exhibit widespread occurrence throughout the region. Grassland shrubland deforestation appears to be spatially clustered, with higher concentrations in the southern and western parts of Sarawak. Smallholder agriculture, while less prevalent, is observed in dispersed locations, primarily in the central and eastern regions. These spatial patterns suggest a heterogeneous distribution of deforestation drivers across the state, potentially influenced by factors such as topography, accessibility, regional policies, or historical land use practices.

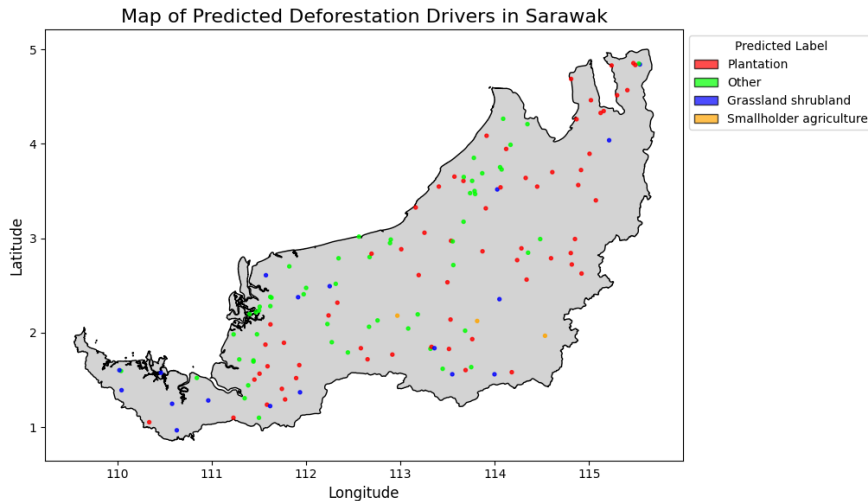


Fig. 4. Map of predicted deforestation drivers in Sarawak.

While direct ground truth validation for Sarawak predictions was not possible due to data limitations, indirect validation performed through visual interpretation of high-resolution satellite imagery and cross-referencing with documented land use changes from local forest reports provide reasonable confidence in the model's predictions. Nonetheless, future work would benefit from ground truth validation.

5. Discussion

The research findings contribute to the growing body of literature on remote sensing-based deforestation driver classification in Southeast Asia. The performance of trained models, particularly EfficientNet, aligns with recent studies employing deep learning techniques for land cover classification [10], particularly in handling the complex spectral and temporal patterns characteristic of tropical forest landscapes. Our achieved accuracy of 65%, while lower than 72% reported in [16], is noteworthy considering the challenges of cross-regional transfer learning and the smaller publicly available training dataset. The model performance reflects the inherent complexity of distinguishing between similar land use transitions where factors such as cloud cover and seasonal variations can significantly impact classification accuracy.

The transferability of our model from Indonesian training data to Sarawak test data suggests some common patterns in deforestation drivers across the region, supporting previous comparative studies [2]. These patterns notably include the prevalence of industrial-scale plantations, particularly oil palm establishments, as the dominant

driver of forest conversion. This finding aligns with the historical trends documented by Gaveau et al. [2] who found that 76% deforestation in Malaysian Borneo was associated with industrial plantations.

The dominance of plantation-driven deforestation (45.7% of cases) in our Sarawak predictions corroborates existing research on the expansion of oil palm and timber plantations in the region.

The temporal shift observed from 2017 to 2018, with decreases in Grassland/shrubland predictions and increases in Other and Smallholder agriculture categories, may indicate evolving land use patterns or reflect the challenges in distinguishing between these categories using remote sensing data alone.

The study demonstrates the potential of deep learning models, particularly EfficientNet, in classifying deforestation drivers using multi-temporal Landsat imagery. The ability to transfer knowledge from one geographic context (Indonesia) to another (Sarawak) is particularly significant, as it suggests the possibility of developing more generalized models for tropical forest regions. This could greatly enhance our capacity for large-scale monitoring and understanding of deforestation processes. Despite the promising results, several limitations should be addressed in future research as listed below:

- Lack of regional data for Sarawak: Most geospatial data providers offer national-level data, which may not adequately capture the unique characteristics and patterns of deforestation in Sarawak. The absence of region-specific data limits the model's ability to account for local variations in land use dynamics, potentially affecting its accuracy and applicability to the Sarawak context.
- Limited ground truth data for Sarawak: The model's performance on the Sarawak dataset could not be fully validated due to the lack of ground-truth deforestation driver information. This limitation underscores the critical need for expert annotation in the field of deforestation driver classification. The complex nature of land use changes requires domain expertise to accurately interpret and categorize drivers. The scarcity of such expert-annotated data for Sarawak significantly constrains the study's ability to validate and refine the model effectively.
- Temporal resolution: The annual time step used in the study's analysis may obscure finer-scale temporal dynamics of land cover change. Incorporating higher temporal resolution data, such as from Sentinel-2, could provide more detailed insights into the progression of deforestation and subsequent land use.
- Evaluation metrics and statistical validation: While the study provides accuracy measurements, comprehensive evaluation metrics (precision, recall, F1-scores) and statistical significance testing would be insightful model validation. However, these advanced metrics would be most meaningful when ground truth data for Sarawak becomes available, as they require verified class labels for proper calculation. This underscores the interconnected nature of our current limitations – the lack of regional ground truth data not only affects model validation but also constrains our ability to perform detailed statistical analysis.

Future research directions should therefore prioritize addressing these interconnected limitations while exploring new technological opportunities. The potential of advanced transformer architectures should be investigated to improve the accuracy and efficiency of deforestation driver classification across the entirety of Sarawak's forest loss events as these models have shown promising results in

capturing complex spatial and temporal relationships. This should be coupled with the development of a comprehensive, expertly annotated Sarawak dataset through collaborations with local experts and forest managers. Such ground truth data would enable both detailed statistical analysis and comprehensive metric evaluation. Additionally, leveraging higher resolution satellite imagery could significantly enhance the model's ability to discern fine-grained land use patterns and subtle changes in forest cover. This approach, combined with the integration of multi-spectral and radar data, could provide a more comprehensive and accurate assessment of deforestation drivers in Sarawak whilst addressing the current limitations in temporal resolution and regional data specificity.

6. Conclusions

The study demonstrated the potential of deep learning models, particularly EfficientNet, in classifying deforestation drivers across different geographic contexts in Southeast Asia. By leveraging multi-temporal Landsat imagery and topographic data, models trained on Indonesian data were able to classify deforestation events in Sarawak, Malaysia. The results highlight the prevalence of plantation-driven deforestation in Sarawak, while also revealing temporal shifts in land use patterns between 2017 and 2018. The transferability of the trained model across different geographic contexts represents a significant step towards developing more generalized approaches for monitoring and understanding tropical deforestation at large scales. This capability could greatly enhance the ability to track forest loss and subsequent land use changes, providing valuable insights for policymakers and conservation efforts. As global efforts to combat deforestation intensify, the development of transferable methods for classifying deforestation drivers becomes increasingly crucial. The study contributes to this goal by demonstrating the potential of deep learning approaches in this domain. By continuing to refine these methods and addressing current limitations, we can work towards more effective monitoring and management of our valuable forest resources.

Source Code

The source code developed in this study can be accessed through <https://github.com/AbdullahiHD/Sarawak-Deforestation-Drivers-Classification>.

References

1. Koh, J.; Johari, S.; Shuib, A.; Siow, M.L.; and Matthew, N.K. (2023). Malaysia's forest pledges and the Bornean state of Sarawak: A policy perspective. *Sustainability*, 15(2), 1385.
2. Gaveau, D.L.A. et al. (2016). Rapid conversions and avoided deforestation: Examining four decades of industrial plantation expansion in Borneo. *Scientific Reports*, 6(1), 32017.
3. Austin, K.G.; Schwantes, A.; Gu, Y.; and Kasibhatla, P.S. (2019). What causes deforestation in Indonesia? *Environmental Research Letters*, 14(2), 024007.
4. Bayas, J.C.L. et al. (2022). Drivers of tropical forest loss between 2008 and 2019. *Scientific Data*, 9(1), 146.
5. Hansen, M.C. et al. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, 342(6160), 850-853.

6. Curtis, P.G.; Slay, C.M.; Harris, N.L.; Tyukavina, A.; and Hansen, M.C. (2018). Classifying drivers of global forest loss. *Science*, 361(6407), 1108-1111.
7. Descals, A. et al. (2021). High-resolution global map of smallholder and industrial closed-canopy oil palm plantations. *Earth System Science Data*, 13(3), 1211-1231.
8. Poortinga, A. et al. (2019). Mapping plantations in Myanmar by fusing Landsat-8, Sentinel-2 and Sentinel-1 data along with systematic error quantification. *Remote Sensing*, 11(7), 831.
9. Phang, S.K.; Chiang, T.H.A.; Haponen, A.; and Chang, M.M.L. (2023). From satellite to UAV-based remote sensing: A review on precision agriculture. *IEEE Access*, 11, 127057-127076.
10. Vali, A.; Comai, S.; and Matteucci, M. (2020). Deep learning for land use and land cover classification based on hyperspectral and multispectral earth observation data: A review. *Remote Sensing*, 12(15), 2495.
11. Jabbar, M.T.; Dawood, A.S.; and Al-Tameemi, H.J. (2018). Effect of groundwater salinity level on soil using remote sensing and GIS techniques: Case study of southwest of Basra Province. *Journal of Engineering Science and Technology*, 13(4), 977-989.
12. Sholagberu, A.T.; Mustafa, M.R.; Yusof, K.W.; and Hashim, A.M. (2017). Geo-statistical based susceptibility mapping of soil erosion and optimization of its causative factors: A conceptual framework. *Journal of Engineering Science and Technology*, 12(11), 2880-2895.
13. Hethcoat, M.G. et al. (2019). A machine learning approach to map tropical selective logging. *Remote Sensing of Environment*, 221, 569-582.
14. Chen, H.; Qi, Z.; and Shi, Z. (2022). Remote sensing image change detection with transformers. *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1-14.
15. Masolele, R.N. et al. (2021). Spatial and temporal deep learning methods for deriving land-use following deforestation: A pan-tropical case study using Landsat time series. *Remote Sensing of Environment*, 264, 112600.
16. Ramachandran, N. et al. (2024). Automatic deforestation driver attribution using deep learning on satellite imagery. *Global Environmental Change*, 86, 102843.
17. Ronneberger, O.; Fischer, P.; and Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. *Proceedings of the Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, Munich, Germany, 234-241.
18. Dosovitskiy, A. et al. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 1-22.
19. Wang, G.; Li, B.; Zhang, X.; and Zhang, S. (2022). A network combining a transformer and a convolutional neural network for remote sensing image change detection. *Remote Sensing*, 14(9), 2228.
20. Chen, T.; Kornblith, S.; Norouzi, M.; and Hinton, G. (2020). A simple framework for contrastive learning of visual representations. *Proceedings of the International Conference on Machine Learning*, Virtual Conference, 1597-1607.
21. Steiner, A. et al. (2021). How to train your ViT? Data, augmentation, and regularization in vision transformers. *Transactions of Machine Learning Research. arXiv preprint arXiv:2106.10270*, 1-16.