

Model Transferability of Land Cover Classification: Comparing Laos and Malaysia



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Abstract

Large-scale land cover (LC) classification requires extensive training data, robust algorithms, and high computational power. Cloud platforms such as Google Earth Engine (GEE) enable efficient processing of large datasets, but maintaining consistent training samples remains challenging due to rapid vegetation change and limited field data. This study evaluates the potential of transfer learning to reuse training datasets across time in two contrasting regions of Southeast Asia: Luang Namtha (Northern Laos) and Sabah (Malaysian Borneo). Training data were collected from field surveys and high-resolution imagery, and LC classification was conducted using a Random Forest model in GEE. Reference scenario accuracies reached 0.93 in Luang Namtha and 0.90 in Sabah, with reduced accuracy in transfer scenarios. Forest classes in both regions and mangroves in Sabah showed stable F-scores across scenarios. However, the commodity plantation classes such as rubber, oil palm, and tree plantation has not yet achieve desirable result in transfer scenarios. This approach supports more efficient monitoring of plantation establishment and expansion, which is critical for assessing ecological and social impacts.

INTRODUCTION

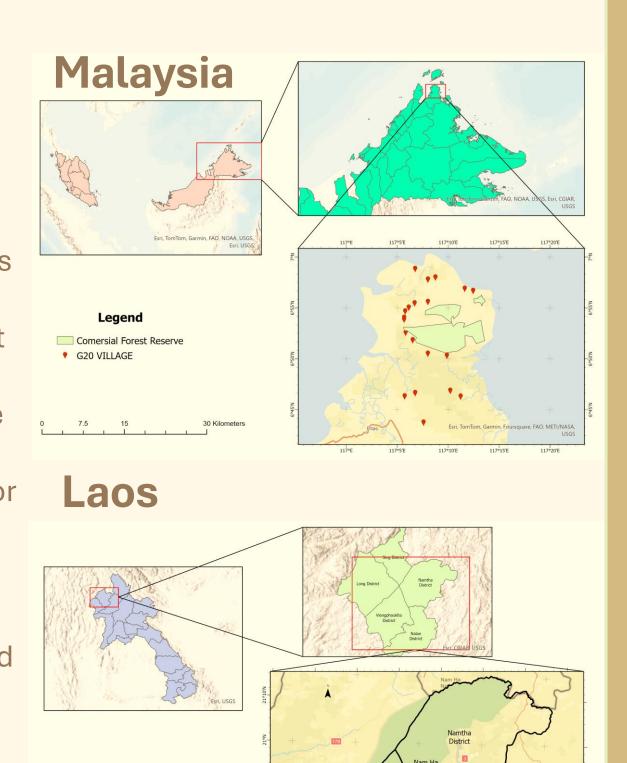
Background

- Advances in cloud computing platforms like Google Earth Engine now enable large-scale LC mapping using multisource remote sensing data.
- High-quality training samples remain a major challenge, as field surveys and manual labeling are costly and time-consuming.
- Transfer learning offers a way to reuse existing training data across years, reducing the need for new data collection.
- Despite being one of the main driver of deforestation in Southeast Asia, commodity plantation (e.g Oil palm, rubber, timber plantation) are often "undetected in land cover product as they're treated as forest or tree cover classes
- Understanding model transferability for these classes is crucial for improving deforestation monitoring and producing more detailed LC maps.

Objectives

to understand transferability performance in classification of tree and commodity plantations in the tropical forest landscape.

- Assess how reliably land-cover classification models transfer across predominantly vegetated regions.
- Identify the factors that influence or support successful model transferability.
- Evaluate which land-cover classes—especially tree and commodity plantations—perform well or poorly in different transfer scenarios.



METHOD 2007,2015,2024 Landsat 5/8 Atmospheric Spectral Band Spectral Indices Terrain algorithm **Google Earth** Correction Selection calculation **Engine** NDVI, EVI,SAVI, Relflectance of Cloud Masking Elevation Aspect Band 2-7 nBR. MNDWI Landsat Imagery Mosaic Data fusion Development RF Training Point **Random Forest** Field Survey Algorithm Pseudo Invariant Model Transfer for Classification for Features Matching Reference Point Transfer Scenario Reference Scenario Google Earth, Planet NICFI Validation Point for Imagery Un-chaged Land Validation Point Transfer Scenario Transfer Scenario Reference Scenario LC Map LC Map

Methodology

- We compare 2 study research site mountainous and coastal swampy area with both experienced forest conversion to plantation.
- Sample point collected through field survey (GPS marking and interview) and Visual interpretation from High resolution imagery
- We use Random "Forest Machine" Learning to classify land cover in research site. Train the model how to classify land cover map.

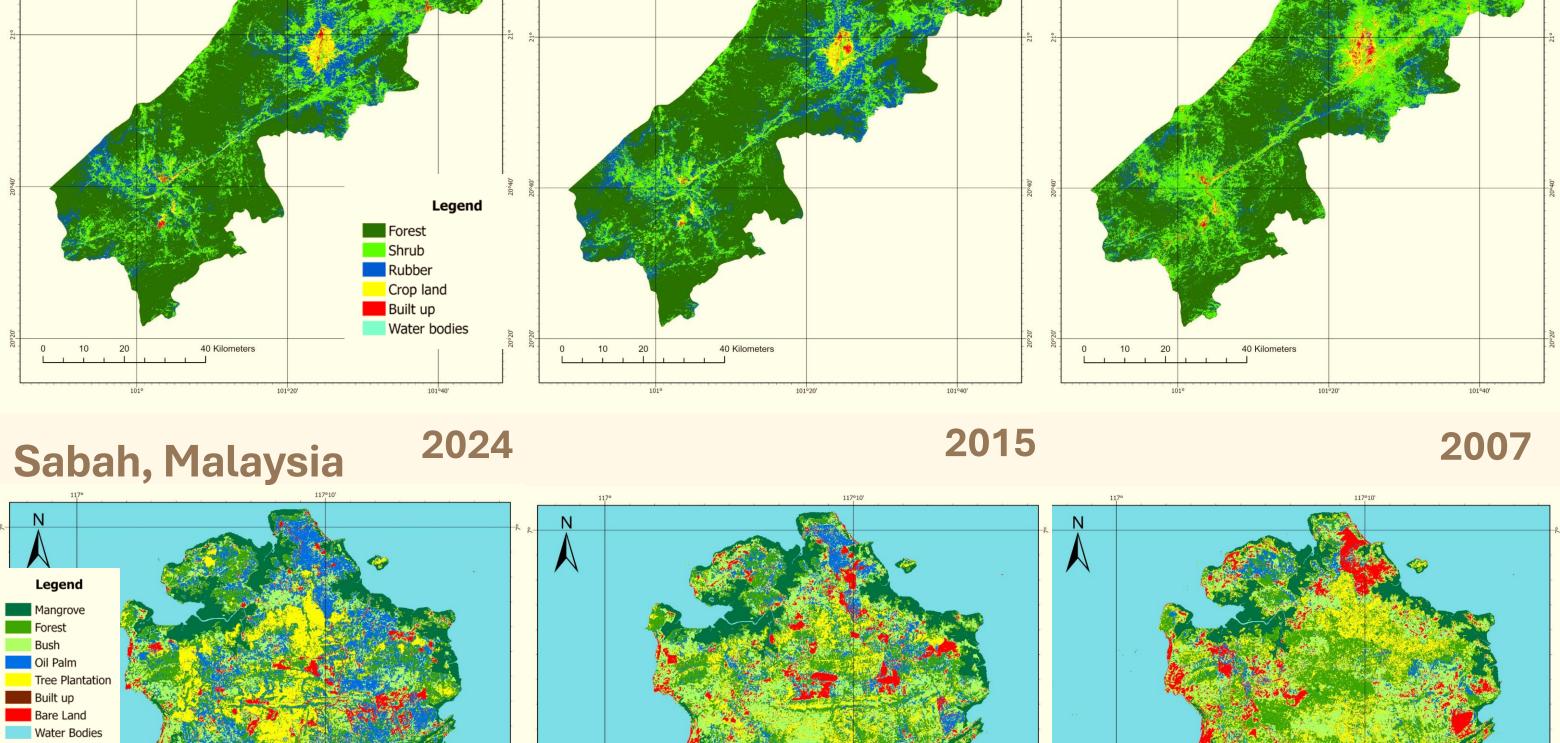
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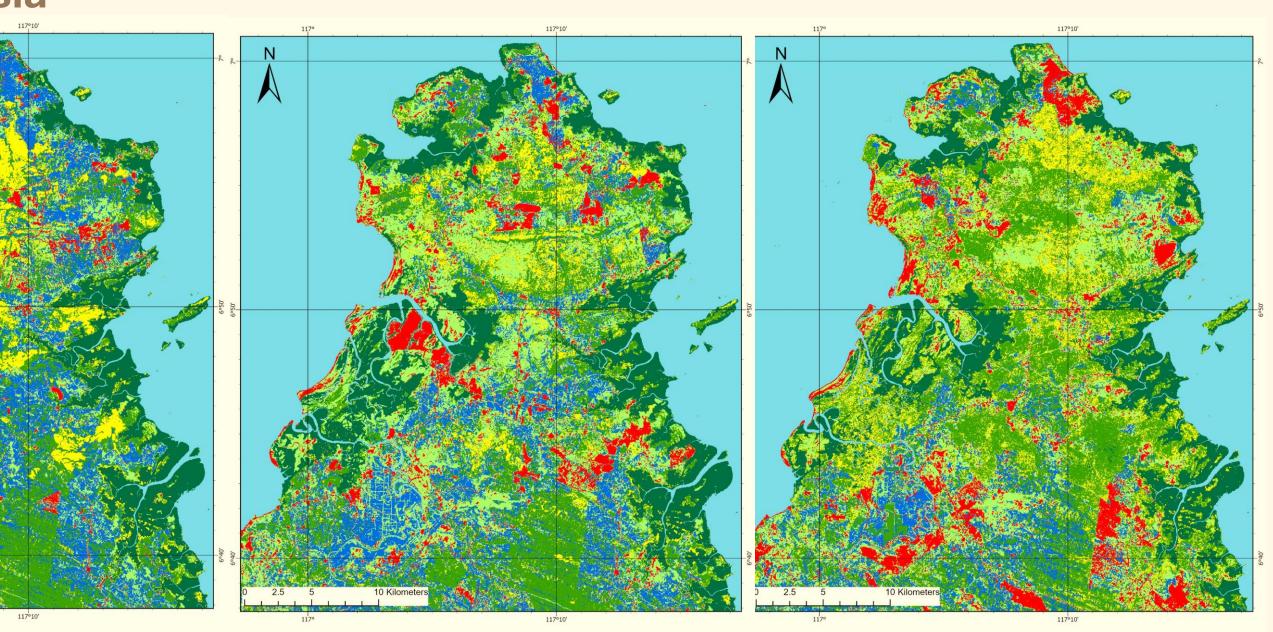
- We used the model train in year 2024 (reference scenario) to classify land cover in 2015 and 2007

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- (transfer scenario.
- The model used in reference year was transferred to classify into different year without training point

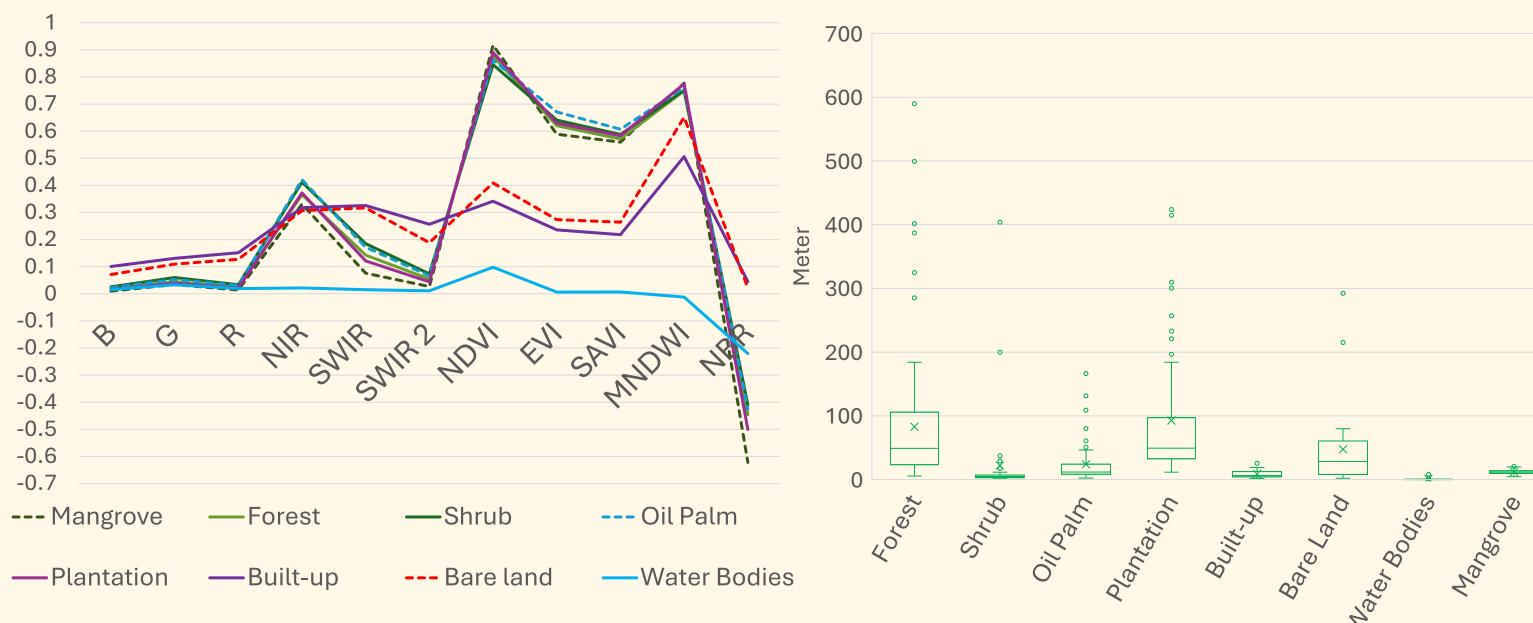
RESULT

Luang Namtha, Laos





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	Crop land —Built up —Water Bodies	Forest Shrub Rubber Crop Land Built-up Water Bodies					
	Spectral Signature	Box of Whisk of elevation					
1		700					
0.9							
0.8		600 .					
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0.5		500					
0.4							
0.3		8					



Accuracy									
Assessment	2024			2015			2007		
	F-Score	precision	Recall	F-Score	precision	recall	F-Score	precision	recall
Luang Namtha									
Forest	0.94	0.91	0.97	0.88	0.84	0.93	0.96	0.96	0.96
Shrub	0.84	0.93	0.76	0.76	0.84	0.70	0.79	0.85	0.73
Rubber	0.96	0.93	0.98	0.94	0.88	1.00	No data	No data	No data
Crop land	0.91	0.89	0.93	0.80	0.90	0.72	0.74	0.83	0.67
Built-up	0.97	0.98	0.96	0.82	0.78	0.88	0.77	0.67	0.91
Water bodies	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Sabah									
Forest	0.85	0.79	0.93	0.82	0.76	0.89	0.56	0.49	0.67
Mangrove	0.96	1.00	0.92	0.98	1.00	0.97	0.95	0.96	0.93
Shrub	0.89	0.93	0.86	0.89	0.87	0.91	0.60	0.82	0.47
Oil Palm	0.84	0.82	0.87	0.72	0.67	0.78	0.44	0.38	0.53
Plantation	0.86	0.91	0.81	0.45	0.71	0.33	0.36	0.45	0.29
Built up	0.89	0.80	1.00	0.80	0.80	0.80	0.37	0.60	0.27
Bareland	0.94	1.00	0.88	0.71	0.75	0.67	0.48	0.38	0.63
Water	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	0.96

Conclusion

- Model transferability works well for land-cover classes with stable, distinct spectral signatures (e.g., water, bare land, built-up).
- Vegetation classes vary more, though mangroves show strong transfer performance.
- Transfer learning can reduce the need for new training data, but accuracy drops when sensors differ or vegetation changes rapidly.
- Future improvements should integrate radar data, domain-adaptation methods, and updated sample points.
- Despite limitations, this approach supports cost-effective monitoring of plantation landscapes and their ecological impacts.

How is this study relevant?

- Reliable model transferability can reduce the need of costly of field survey
- Understanding which land-cover classes transfer well improves accuracy in regions with limited data and difficult access.
- The findings support the development of **more detailed, continuous land-cover products**, enabling better monitoring of ecological and social impacts.