Impacts of Out-Migration on Deforestation: Evidence from Myanmar

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Motivation

This research rises from a counterintuitive idea.

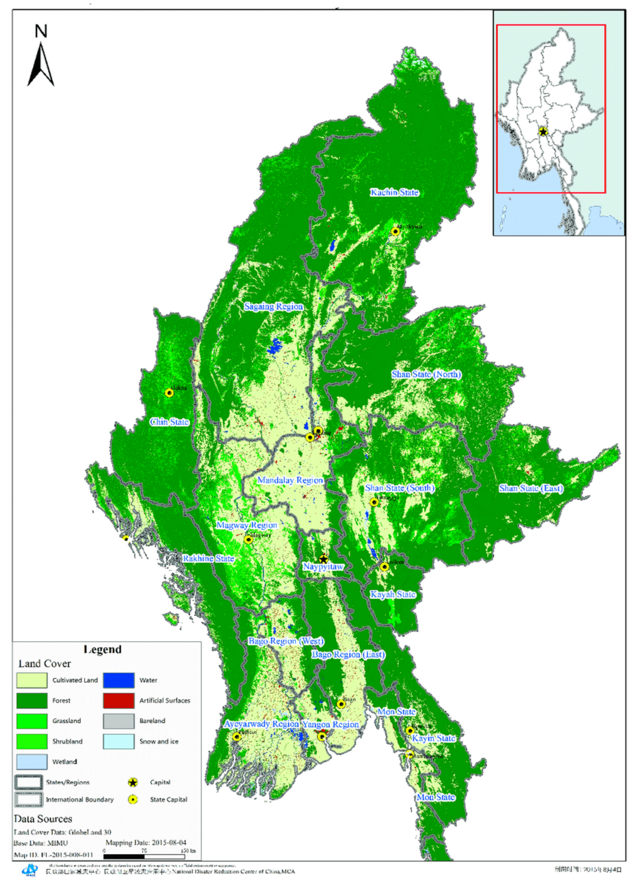
- In common sense, out-migration should lead to fewer forest losses because of the drop in consumption. However, is it true?
- we have observed large scale of constructions, which consumes woods, in rural areas where out-migration is common. One reasonable explanation is that out-migration leads to cash inflow, which supports building new houses and other infrastructures.

Hence, in this research, we dedicate to exploring whether deforestation has a positive or negative impact on deforestation and what is the policy implication of our findings on forest preservation.

Background

Myanmar is a developing country in South-eastern Asia, and it has one of the most considerable forest cover rates globally. Out-migration to Thailand is popular in Myanmar, especially after the political reform, making it a good fit for studying our topic. Following are some facts about Myanmar:

- population: 54,409,800
- GDP per apita: 1400.22 (2020 dollar)
- forest cover rate: 48.3% (source: FAO)
- By 2014, more than 2 million Burmese migrated aboard
- 70.2% of all migrants were in Thailand.



Data

The household-level survey datasets, including migration status, location, and other characteristics, are kindly provided by IFPRI. Fortunately, the popularization of high-resolution satellite remote sensing technology for monitoring the environment enables us to collect household-level environmental data, such as deforestation, precipitation, wind speed, and soil temperature.

We collect the data following two steps; firstly, by having the geographical coordinates for each household, we create a buffer with a radius of 1 km for each household. And then, by analyzing satellite remote sensing images, we acquire the required environmental data, which happened within the buffer for each household from 2000 to 2015. (We stop at the year 2015 because the migration data ends at 2015.)

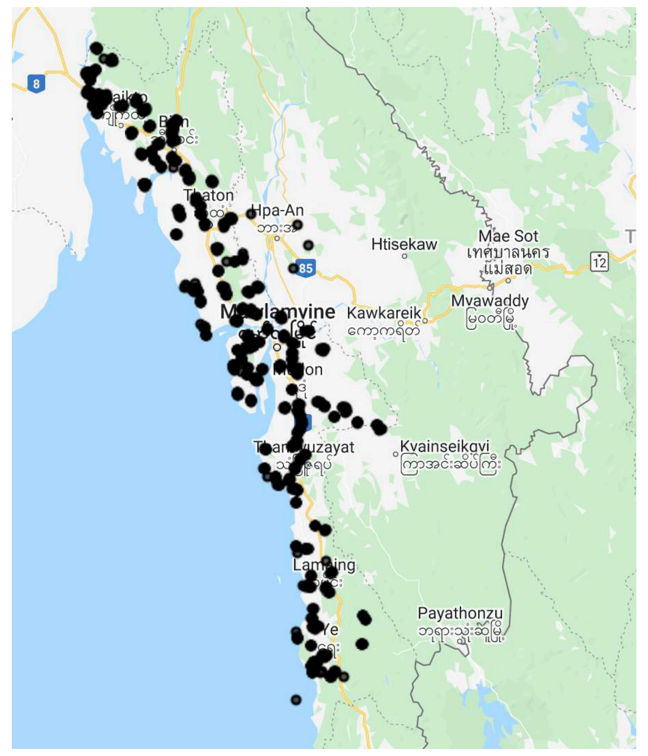


Figure 1. Household locations

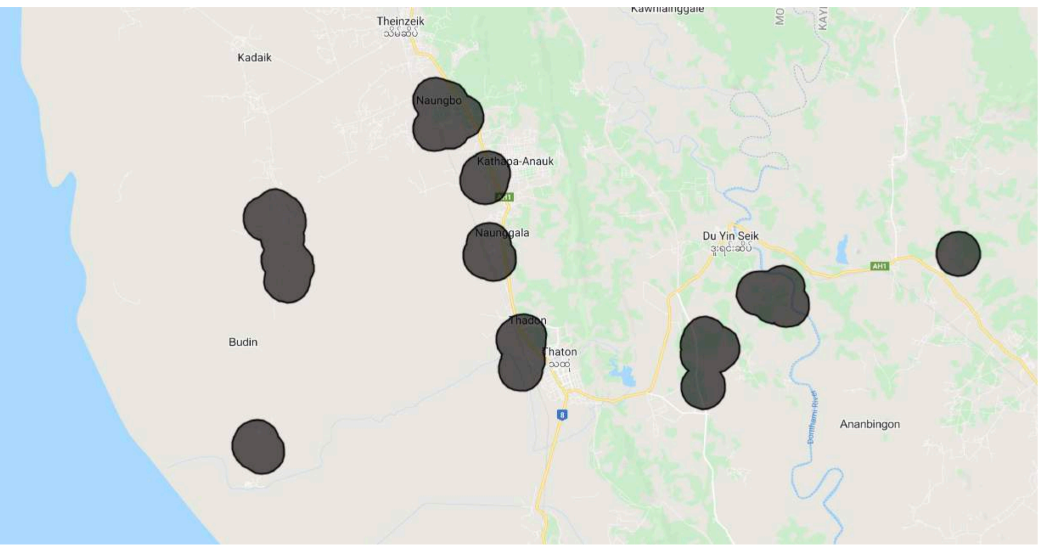


Figure 2. A example of buffers

Methodology

To provide solid and robust analysis, we adopt both spatial autoregressive and autoregressive models.

$$
\begin{aligned}
Deforestation_{i,t} = {} & \lambda_1 W_i * Deforestation_{it} + \sum_{k=1}^{2} \delta_k Deforestation_{i,t-k} \\
& + \beta_1 Migleft_{i,t} + \beta_2 Migback_{i,t} + \beta_3 Eastwind_{i,t} + \beta_4 Northwind_{i,t} \\
& + \beta_5 Precipitation_{i,t} + \beta_6 Cropland_{i,t} + \beta_7 Temp_{i,t} \\
& + \delta_i + \theta_t + \epsilon_{i,t}, t = 1, 2, \cdots, 15
\end{aligned} \tag{1}
$$

Equation (1) is the spatial autoregressive model with fixed effects. We model the spatial dependency for deforestation by designing a spatial autoregressive term to address the buffer overlap problems. It is the matrix multiplication of the standardized weight matrix and the deforestation data. For each household, The weights are assigned based on the area of buffer overlap with its' neighbors.

let D denote the distance between two households,

$$W_i = \frac{1000(1000\theta - Dsin(\frac{\theta}{2})}{\sum_i 1000(1000\theta - Dsin(\frac{\theta}{2}))}$$

where $\theta = 2arccos(D/2)$

Methodology (continued)

Model (2) is the autoregressive model (AR(2)) with fixed effects. It serves as a robustness check.

$$
\begin{aligned}
Deforestation_{i,t} = {} & \sum_{k=1}^{2} \delta_k Deforestation_{i,t-k} \\
& + \beta_1 Migleft_{i,t} + \beta_2 Migback_{i,t} + \beta_3 Eastwind_{i,t} + \beta_4 Northwind_{i,t} \\
& + \beta_5 Precipitation_{i,t} + \beta_6 Cropland_{i,t} + \beta_7 Temp_{i,t} \\
& + \delta_i + \theta_t + \epsilon_{i,t}, t = 1, 2, \cdots, 15
\end{aligned} \tag{2}
$$

Results

Table 1. effects of out&return migration on deforestation(Spatial Autoregressive and Autoregressive models)

	SAR (GMM)			AR (GMM)		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Deforestation_{t-1}$	-0.0278 (0.072)	−0.058 (0.077)	0.020 (0.061)	-0.026 (0.071)	-0.056 (0.076)	0.022 (0.061)
$Deforestation_{t-2}$	-0.118 (0.096)	-0.141 (0.101)		-0.120 (0.097)	-0.143 (0.101)	
W_i∗Deforestation	-0.127* (0.072)	-0.118* (0.071)	-0.145* (0.075)			
Total out migration	-25102*** (8723.8)	-23685*** (7047.1)	-21185*** (7712.1)	-25260*** (8714.4)	-23911*** (7127.5)	-21162*** (7745.2)
Total return migration		-15894 (18454)	-14773 (14123)		-16484 (18544)	-15199 (14123)
Eastwind	79993 (90499)	78006 (76486)	90707 (86747)	63675 (88189)	64059 (74334)	77085 (85925)
Northwind	-40435 (141820)	-33348 (135250)	-97741 (127990)	-22737 (137850)	-15860 (129450)	-80964 (121310)
Precipitation	19.433** (9.381)	21.639*** (8.025)	2.613 (17.608)	18.849** (9.328)	21.364*** (7.964)	2.216 (16.806)
Cropland area	-0.027 (0.018)	-0.019 (0.0176)	-0.015 (0.017)	-0.026 (0.017)	-0.018 (0.018)	-0.014 (0.016)
Soil temperature	48303 (38020)	38849 (37775)	30366 (34315)	49727 (37889)	38444 (38225)	30717 (34557)
Sargan test	chisq(205) = 119.062 (p-value = 1)	chisq(308) = 111.049 (p-value = 1)	chisq(312) = 119.1738 (p-value = 1)	chisq(205) = 118.478 (p-value = 1)	chisq(308) = 110.450 (p-value = 1)	chisq(312) = 119.4731 (p-value = 1)
Autocorrelation test (1)	normal = -3.538 (p-value = 0.000)	normal = -3.792 (p-value = 0.000)	normal = -3.939 (p-value = 0.000)	normal = -3.493 (p-value = 0.000)	normal = -3.758 (p-value = 0.000)	normal = -3.908 (p-value = 0.000)
Autocorrelation test (2)	normal = -0.469 (p-value = 0.639)	normal = -0.354 (p-value = 0.723)	normal = -1.334 (p-value = 0.182)	normal = -0.428 (p-value = 0.668)	normal = -0.339 (p-value = 0.734)	normal = -1.299 (p-value = 0.194)
Wald test for coefficients	chisq(9) = 31.722 (p-value = 0.000)	chisq(10) = 39.191 (p-value = 0.000)	chisq(9) = 28.379 (p-value = 0.001)	chisq(8) = 23.066 (p-value = 0.003)	chisq(9) = 31.688 (p-value = 0.000)	chisq(8) = 14.260 (p-value = 0.075)
Wald test for time dummies	chisq(13) = 96.26 (p-value = 0.000)	chisq(13) = 110.863 (p-value = 0.000)	chisq(14) = 107.839 (p-value = 0.000)	chisq(13) = 105.302 (p-value = 0.00))	chisq(13) = 124.771 (p-value = 0.000)	chisq(14) = 121.559 (p-value = 0.000)

Notes: Unless otherwise noted, standard errors are shown in parentheses.
* Significant at 10% level. ** Significant at 5% level.
*** Significant at 1% level

Conclusion and Discussions

- In short run, out-migration tends to retard forest loss around the households.
- Due to data limitation, long run impacts of out-migration on deforestation remain unclear.

Even though from our results, we can conclude that out-migration could retard deforestation, it does not disprove the counterintuitive idea that out-migration leads to an increase in construction, which worsens the forest loss. One potential reason is that the lumbers used for construction are not necessarily come from the forest near the household. In fact, given the high-quality requirement for construction lumber, it is likely to be cut from deep woods, where trees are more robust. Hence, to test this hypothesis, in the future, we are going to reveal the relationship between out-migration and house size so do housing quality by adopting the deep learning technique.

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