Cease and Disperse: The unintended effect of Indonesia's moratorium on deforestation

Dan Hammer

November 30, 2012

Abstract

This paper examines the impact of the 2011 Indonesian moratorium on the spatial distribution of deforestation. We take advantage of the national border that splits the island of Borneo into Malaysia and Indonesia, and examine the composition of incremental deforestation. Specifically, we track the proportion of newly cleared areas that are in new clusters, rather than on the periphery of existing clusters. We find that the moratorium reduced responsiveness of the creation of new clusters to relevant agricultural prices. However, we also find that the overall rate of deforestation increased, even after controlling for agricultural prices, suggesting that developers merely shifted deforestation to the periphery of existing clusters.

Tropical deforestation accounts for roughly 15% of annual carbon emissions, more than the combined emissions from global road, rail, and air transportation [citation needed]. Indonesia and Brazil alone account for over 40% of annual clearing activity. Any viable effort to mitigate climate change must address tropical deforestation, and specifically clearing activity in Indonesia and Brazil. However, tropical countries tend to be lesser developed, with natural resources as a significant driver of gross domestic product. In Indonesia, for example, it is estimated that the forestry sector accounts for 4% of annual GDP and 5% of national employment. There exist incentives at every level to convert standing forest to financially productive land. Conservation policies therefore face many serious complications, including the ability to monitor and enforce regulation, along with issues of leakage, permanence, and additionality.

The evaluation of conservation policies have been severely limited by lack of timely data on deforestation. Chomitz and Nelson (2011) have shown that strict protected areas are less effective at managing forests than multi-use or indigenous areas, where local actors have a vested interest in the long-term management of forests. The authors were forced to use fires as a proxy for deforestation, since data on deforestation in the tropics was only available at five year intervals. The results may be subject to systematic measurement error across the sample countries, especially since the use of fires to clear forests differ dramatically by region. Other studies have shown the relationship between deforestation and infrastructure development, using the results to illustrate the tradeoff between development and conservation [citations]. But the study of forest resource use has been largely theoretical, relying on the study of the time-optimal path of extraction.

In this paper, we use an original data set on tropical forest clearing activity for each 16-day interval at 500-meter resolution to examine the impact of a 2011 moratorium on new concessions for deforestation in Indonesia. We rely on basic theory of resource extraction through space and time from Weitzman (1980) and Kemp *et al.* (1986) to model the impact of uncertainty of returns on the decision to move to a new resource pool (and incur the set-up costs of doing so). The remainder of the paper is organized as follows: (1) describe the Indonesian moratorium on deforestation, (2) describe the data on deforestation, and why it differs from existing data products to support this type of study, (3) present the empirical strategy and (4) the results of the impact evaluation. Finally, we (5) suggest possible implications of the study, and its importance in broader conservation policy formulation.

Regulatory background

The United Nations has responded to carbon emissions from land conversion by establishing the Reduced Emissions from Deforestation and Degradation (REDD) intitiative in September 2008. With an initial capitalization of \$117.6 million by July 2012, the objective of the REDD initiative is to "support countries' efforts to ... transform their forest sectors so as to contribute to human well-being and meet climate change mitigation and adaptation aspirations ... through performance-based payments." This (paraphrased) mission statement is exceedingly vague; and prospects for a comprehensive, global REDD program have begun to dwindle among the bundle of red tape. Instead, bilateral agreements under the REDD framework are beginning to take shape, most notably Norway's pledge to support Indonesia's pledge to reduce carbon emissions by 26% between 2010 and 2020. With 80% of Indonesian carbon emissions emanating from land use change, Norway has promised US\$1 billion in aid, most of which is contingent on verified emissions reductions from forest conversion. The first stage of the partnership has been the two-year suspension of new concessions for natural forest conversion. The total area affected by the moratorium amounts to 64 million hectares, roughly twice the size of Great Britain [citation].

The moratorium was announced in May of 2010, and was supposed to take effect in January 2011, but after significant opposition from both environmental and industrial groups — arguing from polar extremes — the moratorium was not actually enacted until May 2011. The extent of the moratorium is far from settled; and, in fact, every six months a *new* map of the affected forests is released. The uncertainty is non-trivial, and likely has implications for the spatial patterns of deforestation, since there exist large scale economies associated with clearing forest for agriculture.

Data

We constructed a measure of forest clearing activity for each 500-meter pixel and for each 16-day interval between January 1, 2008 and September 23, 2012 for Indonesian and Malaysian Borneo. The methodology to identify deforestation from satellite imagery is described in a forthcoming paper by Hammer, *et al.* (2012). Each pixel is assigned a normalized, strength-of-signal measure of deforestation, based on the spectral signals from NASA's Moderate Resolution Image Spectrometer (MODIS) sensor on the Terra satellite. A pixel is considered to be affected by foresst clearing activity when the signal first registers above 50%. Only pixels with sufficiently high vegetation per the Vegetation Continuous Field index (0.25 or greater) in February 2000, the first period observed by the MODIS sensor, are used in the analysis. The deforestation data constitute a panel with $N = 2,384,095$ and $T = 109$, a total of about 260 million observations.[1] By the end of the study period, $207,578$ pixels registered above the 50% confidence threshold in Borneo, which implies that 8.71% of forested pixels have been subject to clearing activity between February 2000 and September 2012. For reference, only 29% of forested area in Indonesia remained untouched by forest clearing activity in 2010 from baseline area estimates in 1900.

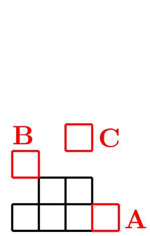


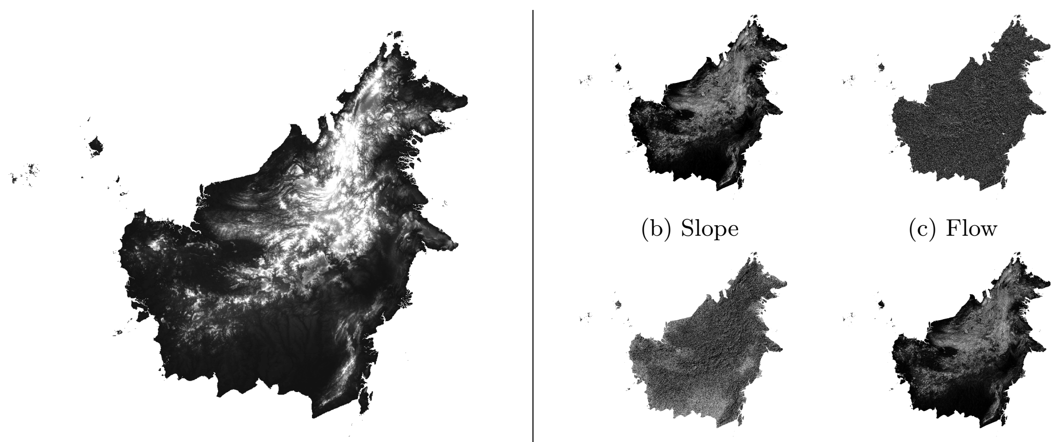
Figure 1: Illustration of clusters

When a pixel first registers above the confidence threshold, they are grouped into one of two types of deforestation: (1) pixels that consitute a new cluster of deforestation, and (2) pixels on the periphery of previously

[1] Note that the study area does not include any pixels in Brunei to make the study more compact, since the total area of Brunei amounts to about 1% of Borneo.

cleared clusters of deforestation. Consider, for example, the illustration in Figure 4. The black, unlabeled pixels represent an existing cluster and the red, labeled pixels indicate newly cleared areas. Within the five pixels that just registered clearing activity, the problem of spliting them into groups (1) and (2) depends crucially on the distance between centroids of the pixels. We rely on the single-linkage hierarchical clustering algorithm to split the new deforestation into groups, setting the distance threshold that would group pixels **C** and **B** along with **A** into the second group, on the periphery of an existing cluster. Single-linkage admits clusters that are characterized by a line, as long as each pixel is only separated by one pixel or less. In Figure 4, only pixels **D** and **E** are considered to have started a new cluster. The subsequent results are robust to different buffer lengths (read: definitions of a cluster by the Euclidean metric).[2]

We also utilize data on daily agricultural prices, mainly the international price of oil palm, which constitutes the main agricultural product in Borneo. Data on rainfall are processed from the NOAA's Precipitation Reconstruction over Land (PREC/L) data set, which provides a relatively coarse grid of precipitation meatures (0.5 degree resolution) at monthly intervals. Characteristics of the land, such as elevation, slope, and water accumulation, are derived and resampled from the 90m resolution Shuttle Radar Topography Mission (SRTM) topographic data set. The SRTM elevation and derived data sets are shown in Figure 2. All derived data sets are derived using the Spatial Analyst extension in ArcGIS, which is especially useful for modeling hydrological features like the level of water accumulation at high resolution. These data sets are highly detailed, as is evidenced by the zoomed image in Figure 3.



(a) Elevation (b) Slope (c) Flow (d) Aspect (e) Drop

Figure 2: Map of the digital elevation model (left) with derived data sets (right) indicating slope, hydrology, and terrain roughness, 90m resolution.

Empirical strategy

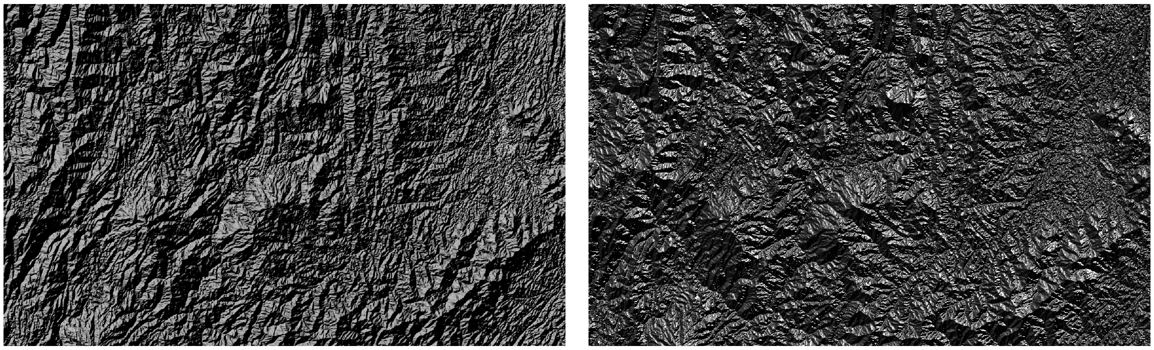
Results

Policy implications

Outline

1. The moratorium restricts new clusters of clearing activity.

[2]Specifically, the broad trends in deforestation are the over a range of buffer lengths, but there are interesting differences — especially in the error structure — in comparing the results of various cluster specifications.



(a) Hillshade (b) Flow direction

Figure 3: Detailed images of two derived data sets for the same area.

2. The price responsiveness of Type 2 clearing has gone down, whereas the total rate of clearing has gone up.

Introduction

There are conditions such that, as Hartwick, *et al.* (1986, pp. 219) note, the set-up costs will destroy the optimal schedule of extraction. The optimality, here, is not the important part, but rather that there are price and set-up costs conditions such that the second resource pool will not be extracted, given the relatively high set-up costs and the relatively low price. A somewhat higher price, however, will yield a mix of the two resource pools. The current cluster may be extracted up to a point where the marginal cost of extraction is higher than it would have been if both resources pools were being utilized. As soon as the price increases to the point to "turn on" the second resource pool (and incur the set-up costs) then the developer will switch to the new resource pool, and the proportion of new aggregate clearing activity in new clusters will rise (since some clusters will come online that weren't being exploited before, turning off the overexploited resource pools).
Indonesia has become increasingly active in managing its forests, which account for over 10% of the world's remaining tropical forests. This increased oversight is part of a broader trend in Indonesia's shift toward stronger regulation in important economic sectors since the mid-1990s; but the forestry sector has become a central focus with international scrutiny of deforestation as a driver of climate change. The forestry sector in Indonesia contributes about 3.5% to gross domestic product, and employs about 4% of the workforce. Carbon emissions from global deforestation represent over 15% of total annual emissions, more than the global transportation sector. Various international initiatives to reduce the rate of forest clearing have been announced, shot down, announced again, but there is still no unifying approach to addressing global emissions from deforestation. The first major, bilateral pledge that is tied to a reduction in deforestation is between Norway and Indonesia. Norway has promised USD$1 billion in aid if Indonesia is able to reduce its emissions from deforestation.

In response, Indonesia enacted a moratorium on new concessions for the exploitation of primary natural forests and peat lands in May 2011. The moratorium was announced a year prior, and was set to be enacted in January 2011, but was delayed by almost 6 months because of continued arguments about the parameters of the moratorium. The moratorium has been widely attacked as having had no effect on the deforestation rate. The Jakarta Globe reported on the "continuing forest destruction by several companies despite the moratorium" in May 2012, exactly one year into the two-year moratorium. Environmental advocates blame the anemic reduction on a "series of loopholes" and changing concession maps, even after the moratorium was enacted. Every six months, the maps indicating the extent of the moratorium are amended, creating uncertainty that must have economic implications. Additionally, the two-year moratorium does not apply to existing concessions and secondary forests, allowing for new investment and continued development.

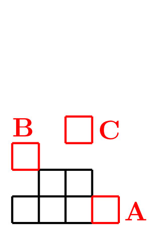


Figure 4: Illustration of clusters

"The worst thing about the moratorium," according to the REDD monitor, "is that it has not reduced deforestation." It is true that the rate of deforestation has increased since May 2011. But it is likely that this opinion is so simple that it misses contours of the economic response to the moratorium that may affect the evaluation of its overall efficacy. The purpose of this paper is to examine the impact of the moratorium on the spatial distribution of deforestation. We split forest clearing activity into two groups based on whether the deforestation results in a new cluster or whether it occurs on the periphery of existing clusters. We find that the moratorium diminished new investment in deforestation clusters, but increased clearing activity on the periphery of existing clusters. The policy focused on one type of clearing activity merely pushed deforestation toward a different class of clearing activity, one that does not require as much upfront investment.

Data

Data on clusters of deforestation is derived from satellite imagery. The spectral signals from the raw imagery are interpreted toward a tractable measure of forest clearing activity; and the flagged pixels are subsequently grouped into discrete clusters using a hierarchical clustering algorithm. Reliable information on forest clearing activity ranges from January 1, 2008 through September 23, 2012. The result is a time series of deforestation that can be decomposed into incremental clearing activity (1) that occurs on the periphery of existing clusters, and (2) that constitute new clusters of deforestation. Consider, for example, the illustration in Figure 4 where the black, unlabeled pixels constitute an existing cluster and the red, labeled pixels indicate newly cleared areas. Within this sample area, the rate of clearing would be five pixels, which can be further decomposed into two groups, based on distance from the existing cluster. The standard specification for analysis throughout the rest of the paper would place pixels **A**, **B**, and **C** on the periphery of the existing cluster and define pixels **D** and **E** as a new cluster. This study attempts to identify the effect of Indonesia's moratorium on the composition of incremental clearing activity, indicated here by 2/5, as well as the effect on the overall rate. The results are robust to different specifications of clusters, which could include pixels **D** and **E** in the existing cluster, depending on the buffer. New pixels clusters require, on average, more up-front investment to clear than pixels on the periphery of existing clusters. We assume economies of scale, with decreasing average costs.

Modeling considerations

Empirical evidence suggests that the cost of extraction is constant within a cluster. That is, pixels deforested at a later time tend to have the same physical attributes (e.g., slope and elevation) as pixels deforested earlier. This indicates constant cost of extraction within a cluster. Between clusters, however, there are increasing costs. Suppose for example that q_1 and q_2 indicate the quantites extracted from clusters 1 and 2, where clearing activity is currently in cluster 1 but not yet in cluster 2. If $C(\cdot)$ is the total cost function, then $C'(q_1) = c_1 < c_2 = C'(q_2)$. This is supported by the data.

We cannot assume that deforestation is a classically exhaustible resource, since the decrease in available (read: profitable) clusters goes down with the moratorium. An exhaustible resource situation would imply that the rate of extraction in current clusters would decrease, since it has to last longer. However, we don't see this. I think that this has to do with the temporary nature of the moratorium, that t_1 is now restricted.

More of the resource in cluster 1 may be consumed before switching – does this imply that the short term rate increases in a discrete way?

What about the factors of "production" of deforestation. If there is a decrease in demand on one type of production, the factors become cheaper for the other – for existing clusters. The lower marginal cost will also mean that more can be produced with factors that had previously been working in higher-cost extraction.

Increase in price implies shorter time frame to switch to new clusters. Higher rate of clearing in new and on the periphery of old clusters. Shorter time frame to switch.
Option value? Storage models?

Empirical strategy

Initial analysis

The attacks on the efficacy of the moratorium often ignore the increased price of palm oil, which peaked in January 2011. The baseline rate of clearing should be conditional on the price of the agricultural products, which drive investment in cleared land, rather than the unconditional, pre-moratorium rate. The palm oil price is charted in Figure **??**. The palm prices track the general trend in global agricultural prices, suggesting that the price increases were exogenous, despite the fact that Indonesian palm oil accounts for about 40% of global supply.

Empirical evidence suggests that the moratorium shifted the spatial distribution of clearing away from the counterfactual. Increases in output price generally increase the spatial dispersion of clearing. A larger proportion of clearing activity takes place in new clusters, rather than on the periphery of existing clusters when the price is high. This makes sense. A higher price will slowly begin to shift developers' expectiations on the return to cleared land, which is an input to production of agricultural products. Assuming a constant and stable marginal cost of clearing, the fixed costs of clearing become more palatable as the price of agricultural products increase: there is more of a chance of a positive return on investment (all in expectation). The proportion of new clearing in *new* clusters, then, will increase with the expected return (price of oil palm) — there is more of a chance that the investment will be made. There will be some lag, some time for developers' expectations to adjust, but even looking at the contemporaneous data, the signal is reasonably clear.

The moratorium reduced the price responsiveness of deforestation in new clusters, relative to old clusters. Less of incremental clearing occurred in new clusters than we would expect, given the sustained and rapid price increase of oil palm. This makes sense, too. The moratorium restricted new concessions for deforestation, but did not restrict clearing activity within existing concessions. On average, only 70% of existing concessions had been cleared; much of the concession area remained untouched, presumably stored for future exploitation [citation needed].

The natural next question is "what are the assumptions that would cause the shift to old clusters to completely offset the overall reduction in new clusters?" The data suggest that the total or overall rate of clearing may have increased after the moratorium was enacted, or equivalently that the *more than offset* the reduction of clearing in new clusters.

Points to make (in no particular order):

1. Tropical deforestation accounts for roughly 15% of annual carbon emissions, more than the combined emissions from road, rail, air, and marine transportation, worldwide.
2. Borneo is 73% Indonesia, 26% Malaysia, and 1% Brunei (which is not considered in this study to keep it compact). It is home to one of the oldest rainforests in the world.
3. The moratorium constrained investment in new deforestation clusters, shifting the spatial distribution of deforestation and ultimately increasing the overall rate of deforestation.

4. Indonesia announced the two-year moratorium in May 2010 to be enacted in January 2011, but it wasn't actually enacted until March 2011 after disputes between government, industry, and environmental advocates. Three stages of the moratorium.

5. The moratorium was catalyzed by a $1 billion promise from Norway, cash on delivery to Indonesia, contingent on a reduction in the deforestation rate. The promise of aid made the government's previously feeble attempts to manage deforestation much more credible.

6. We use the island of Borneo as a social lab, of sorts, given that Malaysian Borneo is similar in weather and agricultural output as Indonesian Borneo, but was not subject to the moratorium. While the border was drawn based on physical attributes of the land – to divide the watersheds – the similarity of the two sides is reasonable. The one complication may be that Indonesian Borneo is three times the size of Malasian Borneo, potentially affecting the possible spatial dispersion.

7. The overall effect of the moratorium was an *increase* in the rate of deforestation, relative to Malaysia, but to decrease the proportion of deforestation due to new clusters. The spatial pattern of deforestation became more condensed, with clearing occuring disproportionately on the periphery of pre-existing clusters.

8. The new paradigm under the moratorium resembles the short-term response to increased supply of cleared land, on the outskirts of existing clusters. Lower cost to clear, no investment. Short-term response to quick changes in the demand for cleared land are met with deforestation near previously cleared clusters.

9. Intertemporal leakage. Induced short-term behavior in place of long-term behavior, potentially waiting out the two-year moratorium. Similar to spatial leakage: Restrictions on clearing in a certain time or place will just induce clearing in a different time or place.

10. The theoretical structure should have the ability to distinguish between alternatives, to select a model based on testable hypotheses: (a) race to the bottom? (b) lower productivity of land near existing clusters? (c) freed up resources due to a lower fixed cost?

11. Use the physical layout of the land to help distinguish between hypotheses. Examine the attributes of the land that was cleared near existing clusters over time, before and after the moratorium was enacted.

12. Potentially cluster the rate-proportion graph, looking to see if the inclusion in each group was sequenced. A different approach to the standard diff-n-diff, potentially providing more intuition about the way the data are clustered through time.

13. Disney has stopped sourcing from suppliers with a poor track record on deforestation.

Model Considerations:

1. Areas around clusters should be modelled with option value, reflecting the fact that short term supply of cleared land is mainly around existing clusters.

2. The return on land cleared around existing clusters is lower than that of new clusters. Thus, to get the same amount of product out of the land, more has to be cleared. **Check this, ask someone else.** Examine the characteristics of land cleared *around existing clusters* to see if the moratorium had an appreciable impact on, say, the slope of cleared land (something related to yield).

3. Dynamic programming problem, with option value and stochastic element. Two types of resources and one investment term that determines the next period's level of new land.

4. Look at the effect of increasing the risk of appropriation associated with new land, drastically lowering the expected return.

5. There is intertia in the data, allow for time to adjust expectations and to realize gains from previous investment.

6. Is the elasticity of supply of cleared land near *existing* clusters greater than the elasticity of supply of cleared land in *new* clusters. Different cost structures of clearing. If so, then a shock in demand will have a more than proportionate effect on the land around existing clusters. (This is seen in the data.) The greater supply elasticity may be due to (a) less time to mobilize resources and (b) excess capacity or inventory of land near existing clusters. Lower marginal costs will imply a greater elasticity of supply.

7. The supply shock that came with restricting new clearing will induce a more than proportionate response in supply (?) Inelastic demand for cleared land. Why doesn't the new supply just flood the market, immediately driving back down the price?

8. Ultimately, the firms will have to invest in new clusters; but they are content to use up their reserves now, knowing that the moratorium is set to expire in May 2013.

Basic results:

1. The moratorium had the unintending consequence of *increasing* short-term clearing activity by shifting the spatial ditribution of deforestation to the periphery of exisiting clusters. Potential cause: lower returns on land around existing clusters, and steady demand for the yield from cleared land.

2. Deforesters are treating the set moratorium period as a short term hit to investment activity, such that they are responding as if there was a short-term increase in the demand for cleared land (which would and has happened in the past). This can be seen from the stratified scatter plots.

3. The implication is that if the moratorium is lifted after two years, then there will be temporal leakage – restricting clearing in one period only pushed it into another. If the moratorium is maintained, however, it may actually reduce long-term clearing, since investment hasn't been made. Another prediction: way more outcry from industry over a long-term moratorium extension than for the initial two-year enactment to respond to the Norwegian aid promise.

4. Much of the effect happens when the moratorium was *supposed* to be enacted, the other half, so far, has occured after the moratorium was *actually* enacted.

Let $x_1(t)$ and $x_2(t)$ be the amount of land cleared in time t, where the subscript 1 indicates that the land is on the periphery of an existing cluster and the 2 indicates that the land constitutes a new cluster. Let $p_1(t)$ and $p_2(t)$ be the respective prices for the cleared land, which are functions of the physical characteristics of the land. We expect that $p_1(t) < p_2(t)$, since new sites of land clearing will tend to locate in land with the highest net return. Landowners will progressively clear less valuable land according to an option value approach, effectively storing the forested land until the return is high enough to merit the marginal cost of clearing. For now, though, consider the simple dynamic programming problem to

$$\max_{x_1, x_2, I} \int_0^T \pi_1(x_1(t)) + \pi_2(x_2(t)) - I(t)\, dt \quad \text{subject to} \quad \dot{R}_2 = f(I(t)) \quad \text{and} \quad \dot{R}_1 = f(I(t-1)) - x_2(t) \tag{1}$$

where $I(t)$ indicates the level of investment in infrastructure or exploration costs in order to create new clusters of cleared land in the following period. For a given amount of land, $\bar{x}$, we assume that $\pi_2(\bar{x}) > \pi_1(\bar{x})$. The profit from the newly cleared land is greater than that of land near older clusters. This gives landowners an extra incentive to clear new land, above and beyond the incentive to expand production. The function f is increasing and maps investment costs into the amount of land available in the new area.

Tables and figures

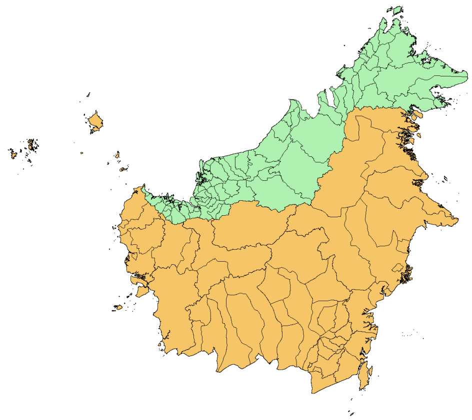


Figure 5: Sample area, Malaysia in green and Indonesia in orange. Borders indicate subprovinces.

Table 1

	Model 1	Model 2	Model 3	Model 4
(Intercept)	368.366***	137.589	447.708***	160.070
	(42.010)	(158.811)	(36.935)	(120.799)
price	0.127***	0.707*	−0.074*	0.652**
	(0.046)	(0.388)	(0.044)	(0.294)
I(price^2)		0.000		0.000**
		(0.000)		(0.000)
cntry			89.029***	89.029***
			(18.103)	(17.884)
post			87.121***	90.026***
			(23.747)	(23.489)
cntry:post			113.321***	113.321***
			(29.884)	(29.523)
R^2	0.033	0.043	0.444	0.460
Adj. R^2	0.029	0.034	0.433	0.447
Num. obs.	218	218	218	218

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

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Table 2

	Model 1	Model 2	Model 3	Model 4
(Intercept)	5.691^{***}	7.992^{***}	6.164^{***}	4.868^{*}
	(0.230)	(0.838)	(0.329)	(2.533)
price	0.427	1.141^{***}	−0.175	0.058
	(0.274)	(0.368)	(0.406)	(0.592)
cntry	2.546^{***}	2.546^{***}	1.541^{***}	8.439^{***}
	(0.114)	(0.112)	(0.465)	(2.770)
post	0.123	0.137	−1.636	−1.463
	(0.149)	(0.146)	(1.233)	(1.211)
cntry:post	-1.249^{***}	-1.249^{***}	2.939^{*}	2.921^{*}
	(0.186)	(0.183)	(1.743)	(1.679)
idn.exch		-27.438^{***}		
		(9.630)		
price:cntry			1.279^{**}	
			(0.575)	
price:post			1.840	1.711
			(1.210)	(1.170)
price:cntry:post			-4.346^{**}	
			(1.712)	
idn.exch:cntry				-66.937^{***}
				(12.899)
mys.exch:neg.cntry				0.331
				(0.641)
cntry:price				2.799^{***}
				(0.782)
cntry:price:post				-4.334^{***}
				(1.635)
R^2	0.741	0.751	0.752	0.781
Adj. R^2	0.736	0.745	0.743	0.771
Num. obs.	214	214	214	214

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

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Table 3

	Model 1	Model 2	Model 3	Model 4
(Intercept)	1264.913^{***}	464.855^{***}	514.937^{***}	398.610^{***}
	(466.868)	(14.549)	(45.413)	(57.746)
date	-0.052			
	(0.032)			
post	149.622^{***}	86.545^{***}	785.999^{***}	591.097^{***}
	(33.555)	(24.017)	(171.078)	(217.539)
cntry		94.159^{***}		232.654^{***}
		(20.576)		(81.665)
cntry:post		35.816		389.805
		(33.965)		(307.647)
price			-3.797	83.778
			(55.765)	(70.909)
price:post			-655.696^{***}	-506.043^{**}
			(167.842)	(213.425)
price:cntry				-175.151^{*}
				(100.281)
price:cntry:post				-299.307
				(301.828)
R^2	0.138	0.277	0.193	0.360
Adj. R^2	0.130	0.267	0.182	0.339
Num. obs.	218	218	218	218

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

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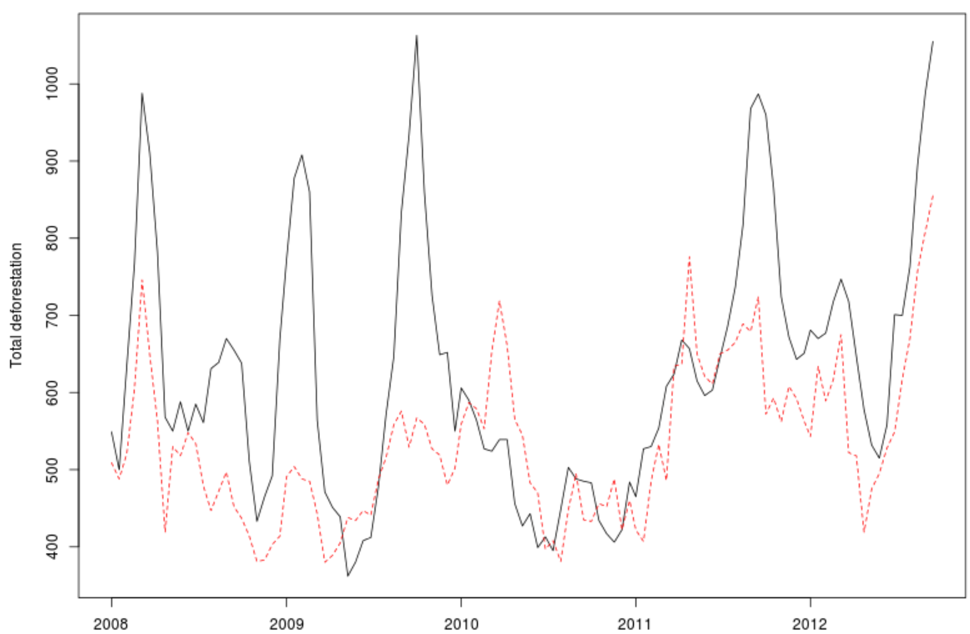
(a) 2-month moving average of proportion measure



(b) Total number of alerts

Figure 6