Coasian Motion: Deforestation and the Central Tendency to Disperse

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Introduction

Deforestation and forest degradation account for 12% of annual carbon emissions, as much as the global transporation sector. An emissions source of this magnitude must be addressed in order to avert severe climate change. International efforts to curb the rate of deforestation have thus far been a series of bilateral agreements, mostly centered around Brazil and Indonesia, the two largest contributors to global deforestation. In 2007, the two countries accounted for approximately 40% of global deforestation. However, as international attention continues to focus on Brazil and Indonesia, forest clearing activity has become more disperesed, especially around the periphery of these regional hotspots. In this paper, we report the broad geographic trends in deforestation, using an original data set on forest clearing activity from satellite imagery. We highlight the increased dispersion of clearing activity and discuss the likely implications for global conservation efforts.

- we care about admin units bc that's where negotiations and policies are crafted and enforced
- defor is clustered

Data

The data used for this paper are the forest clearing alerts from Forest Monitoring for Action (FORMA), a pan-tropical forest monitoring system developed by Hammer et al. (2013). The data are derived from remotely sensed data, primarily from the MODIS sensor. FORMA reports the probability of forest clearing activity at 16-day intervals for each 500-meter, forest pixel in the humid tropics. Pixel time series are created by stacking satellite imagery, merging the spectral histories with ancilliary data, including rainfall. Non-forest pixels are removed from analysis by screening out pixels with VCF < 25 as done in Hansen (2008). The algorithm extracts characteristics from the pixel time series that correspond to unnatural patterns in data. The characteristics are, in turn, matched against the forest cover loss hotspots data set. The result is a continually updated characterization of clearing activity for each period, or a probability of forest clearing activity by the specified time interval.

The accuracy assessment in Hammer et al (2013) indicates that a confidence threshold of 0.5 produces a robust alerting system that minimizes false positives and successfully identifies the industrial-scale clearing activity that is the focus of this paper. The continuous probability range is valuable because it provides information on the relative intensity of clearing across pixels as opposed to a binary indicator. The aggregate measure of clearing activity in an administrative unit in this paper is calculated for each interval as the summed probabilities, conditional on the probabilities exceeding a confidence threshold of 0.5. Analysis of the dynamics of forest clearing acitivity are made possible by the high frequency of the updates. Higher resolultion systems are suitable to focused areal assessments, but cannot adequately characterize the sub-annual dynamics at a time-scale commensurate with economic drivers of deforestation. The dynamics and geographic scope of FORMA data make this paper possible.

Definition of dispersion

Dispersion is the degree of spread of a phenomenon over space and/or time. In this paper, we consider dispersion of deforestation as characterizing the degree of concentration of clearing activity in a geographic area. The measure of dispersion of clearing activity at any particular time is based on an aggregated measure of clearing, given by FORMA. The geographic aggregations of interest in this paper - countries, provinces and sub-provinces - are arbitrary, but important given that these units define the various levels of decision making that affect deforestation.
Let i be the pixel index, and cj be the set of pixel indices in administrative unit j. The aggregate level of clearing activity in administrative unit j and time period t is given by equation X.

$$D_{jt} = \sum_{i \in C_j} \mathbb{I}(p_{it} \geq 0.5) \cdot p_{it} \tag{1}$$

We characterize the spread of clearing activity across all administrative units in the sample by using Shannon's entropy criterion, defined in equation Y.

$$E_t = -\sum_{j=1}^{n} \frac{D_{jt}}{D_t} \log_2 \frac{D_{jt}}{D_t} \quad \text{with} \quad D_t = \sum_j D_{jt} \tag{2}$$

E ranges from 0 to 1, and larger values of E indicate higher dispersion across units. A value of 1 is a uniform distribution, with equal values for all units. A higher value of E across countries, for example, would indicate that clearing is less clustered at the the country level. More concretely, this would indicate that clearing is spreading beyond Brazil and Indonesia.

Geographic dispersion

At various levels of disaggregation, the patterns of forest clearing dispersion remain similar. We consider the country, provincial, and sub-province administrative units because that's where forest management policy is created or implemented.

Country

TODO: why seasonal?

Province and sub-province level

Tree entropy

Look at the dispersion trends *within a country*. This corresponds with the scenario of countries being at international negotiations, who in turn deal with local provinces for actual conservation. How tenable are the promises made at the international negotiating table?

Implications for conservation

Conservation negotiations rely on a series of joint arrangements. Each arrangement takes a significant amount of time to specify. Even if the number of relevant players in the negotiation rises linearly, the number of joint arrangements will rise exponentially. The complexity and barriers to a common conservation agreement increase exponentially as tropical deforestation becomes more dispersed. The basis for this observation is founded in both operations research and contract theory [find citations].

The increased dispersion also suggest the possibility of geographic leakage, given that deforestation has already begun to spread. Static coefficient of friction is much greater than the dyanmic coefficient of friction; and this analogy applies to economic processes with increasing returns to scale.

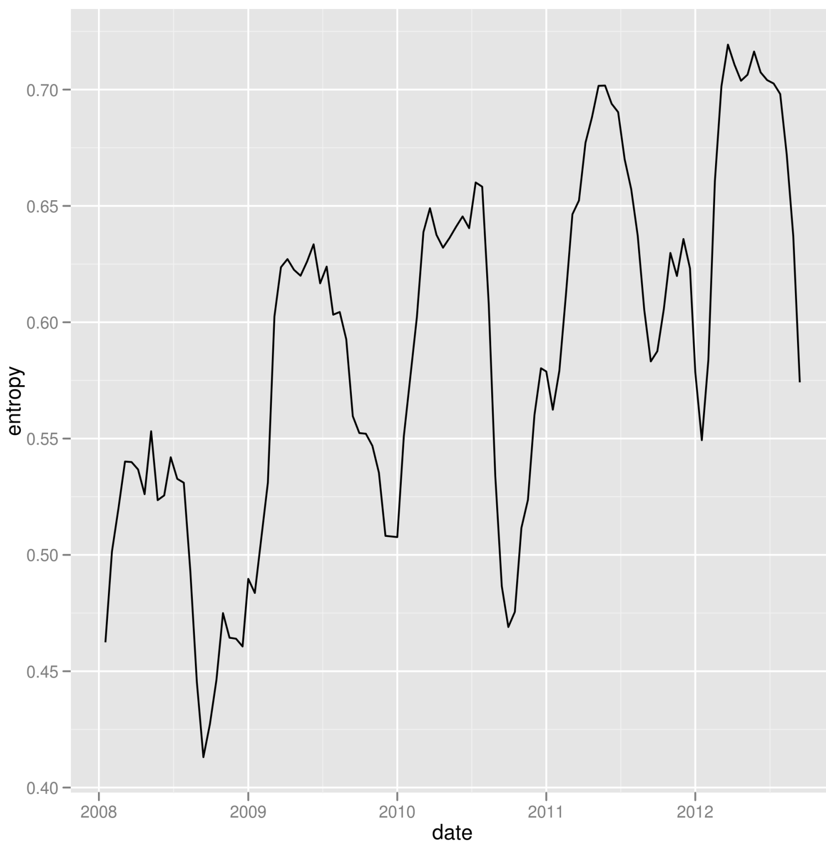

Figure 1: Normalized entropy at the country level between Dec 2005 and Sept 2012.

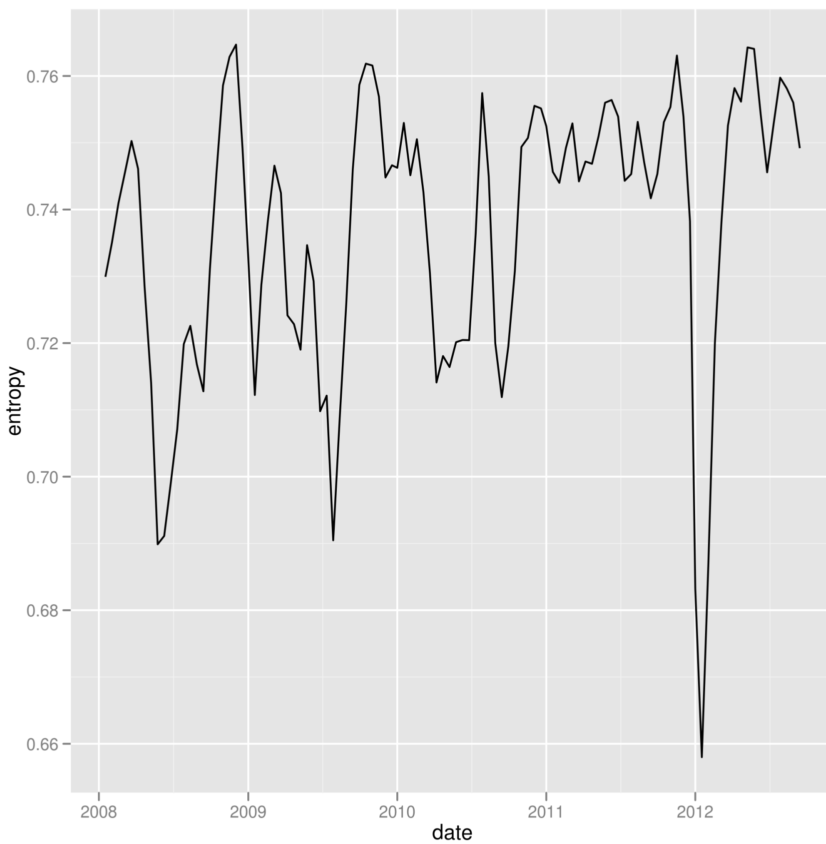

Figure 2: Normalized entropy at the country level between Dec 2005 and Sept 2012.

Conclusion