

Drivers of Deforestation in Indonesia: Spatial Panel Data Analysis

Deforestation has several adverse effects such as global warming, land degradation and soil erosion, loss of biodiversity and ecosystem services, and other indirect socio-economic imbalances (Portela and Rademacher, 2001). It accounts for 6-17% of anthropogenic CO₂ emissions, and about 40% of global greenhouse gases when subsequent land use changes are considered (Baccini et al., 2012, Corbera et al., 2010). To the extent that deforestation causes land use changes that contribute to perilous climate patterns, there are trending global consensus and global and bilateral initiatives to reducing emissions from deforestation and forest degradation (REDD+). However, the dynamics of deforestation is so complex, in both time and space, that the endeavor to understand it has been demanding in terms of data, method, scale and approach.

There are many immediate causes and underlying drivers of deforestation (Angelsen and Kaimowitz, 1999). An important aspect of deforestation is that 'deforestation might cause itself' as, for instance, building roads through a jungle makes the forest more accessible. Despite such spatial feedback loops and potential cycles and trends over time, lack of readily available data has limited our understanding of these dynamics.

This study aims to assess the spatial interaction effect of deforestation and its potential socioeconomic drivers in Indonesian districts. Indonesia is one of the countries with highest carbon reserves in tropical forests and largest emissions from land use change (Corbera et al., 2010). By focusing on sub-national deforestation patterns and district-level interactions, this paper gives insights that pixel level (Wheeler et al., 2013) or more aggregated national analyses (Köthke et al., 2013) would not. Drawing on, but in some aspects departing from, such studies, we use Indonesian districts as units of analysis with actual deforestation (as opposed to forest clearing index).

Two aspects of the variation in deforestation in Indonesia are that, first, time related within-district variation shows average deforestation rose high between 2003 and 2009 until it dropped fast in 2012. Second, there are between district variations that could be attributed to inherent differences in the characteristics of the 167 districts included in this study. These

variations warrant the need to look closely at the spatio-temporal dimensions.

We used district level balanced panel data spanning 2003 to 2012 every 3 years so that we can capture the dynamics while controlling for unobservable heterogeneity. Climate variables for all 167 districts in the study area were extracted from CRU TS3.21, while population and agricultural GDP were obtained from the World Bank's latest INDO-DAPOER (Indonesia Database for Policy and Economic Research). We applied spatial panel econometrics using natural logarithm of deforestation as a dependent variable and GDP (a proxy for economic activities), population density, poverty rate and precipitation along with spatial lags of deforestation as explanatory variables. After observing results from non-spatial pooled and panel models, we computed the *Moran's I* test statistic and found that the spatial weighted averages of deforestation and GDP had significant explanatory power, which points to a more inclusive spatial panel data analysis. A 167x167 contiguity-based spatial weighting matrix was generated using polygon shape files of Indonesia in the GADM database (<http://www.gadm.org/country>).

Among different spatial panel data models, we selected the Spatial Durbin Model (SDM) with random-effects after conducting Hausman and Wald-type tests. This allowed us to find estimates of the direct and indirect effects of the spatial weighted averages of deforestation and GDP. We found that a 10% increase in the spatial weighted average of deforestation leads to about 4% increase in the deforestation of an average district. There are several possible avenues through which these spatial interaction effects can occur. First, roads and other network infrastructure development make remote districts more accessible. The road construction causes deforestation, and once complete and the districts are connected, there comes another round, probably of larger scale, of deforestation in the remote district(s). Second, changes in demand for products that have to do with deforestation are followed by high pressure on forests in neighboring areas. Third, it is possible that political administrative units may also interact strategically, and that strategic interaction might cause the patterns of resource flows to change.

Results also show that higher GDP in an average district is associated with higher deforestation while its spatial lag predicts lower deforestation in neighboring districts. If

GDP goes up by 10%, deforestation is predicted to increase by about 15%, holding other factors equal. This could arise when districts with higher rate of change in GDP invest in sectors that take away land from forest to other land use. Population density was found to have a negative and statistically significant effect on deforestation, which may make sense if the districts with very high population density had barely any forests left, i.e. deforestation had taken place longer ago than the span of this study. Finally, poverty rate - the percentage of people who live below poverty line - is also significant predictor of deforestation. Holding rate of change of GDP equal, higher poverty rate may reflect that economic activities that are unequal might be detrimental to forests, and changes like the Environmental Kuznets Curve (EKC) hypothesis (Bhattarai and Hammig, 2001, Culas, 2012) would be more likely to occur only when districts create equal opportunities for a given GDP.

Though findings show that several factors carry relevant information about how deforestation occurs in Indonesian districts, we stress on the dual benefit of using a spatial panel approach. First, information about deforestation in neighboring spatial units is a statistically significant predictor of deforestation, and projects like REDD+ could improve their prediction of future business-as-usual deforestation scenarios. Second, including spatially weighted average of deforestation in the regression makes statistical inference about the parameters of other explanatory variables more accurate. Therefore, we tentatively conclude that spatial panel data analysis turns out to be superior to either aspatial or cross sectional specifications. The main lesson for REDD+ is that there could be synergy in conservation of forests among neighboring districts though it may not fully solve the problem of leakage.

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