## DATA ANALYSIS

This paper examines a number of variables – culled from scholarly work on deforestation – and questions their relationship to forest cover change in India during the past decade. In academic literature, agricultural pressure, measured in a variety of ways, is routinely identified as a culprit in deforestation. I expand upon this, hypothesizing that coincident with agriculture's negative association with forest growth, greater alternatives in means of living and livelihood should be positively associated with forest cover increases. Put another way, forest expansion is more likely to occur when people have incentives and opportunities to farm less. In addition to the value of agriculture output per capita, I test the value of fishing output per area, urban quality of life, the percent of population that is designated a marginalized socio-religious caste and the number of households per capita claiming government poverty/employment benefits. Population density, a variable whose effect is debated by scholars, is also used specifically as a control variable in several models to tease out significance among other variables.

I do ultimately expect that agricultural output values will be substantially and negatively associated with forest cover growth. Literature would also suggest a negative association between forest cover growth and the percent of people who are denoted as low caste and are therefore less economically and socially mobile; poverty and inequality are thought to lead to desperation which leads to degradation. Meanwhile, I hypothesize variables which measure of the attractiveness of alternative lifestyles and livelihoods — the value of fishing output, urban quality of life and the number of individuals receiving poverty/employment benefits — will be positively associated with forest cover growth.

## BACKGROUND ON VARIABLES

In preparation, a wide number of variables (more than 100) were considered in an initial bivariate analysis. Some were eliminated due to high insignificance, missing observations or strong multicolinearity. Others, though presenting potentially interesting correlations with forest cover change — or, curiously, showing no correlations despite expectations, were simply removed in the interest of brevity. A full list of variables considered is attached as Appendix I. The independent variables used in the following analysis are explained in detail in Table 1.

**Table 1 — Definitions of key variables predicting variation in forest cover**

| *Variable shorthand* | *Variable detail* | *Source:* |
|---|---|---|
| Forest cover change | Percent change of total forest cover, defined as a tree canopy of greater than 10 percent, according to remote sensing data between 2000 and 2009 | Forest Survey of India's State of Forest Report 2001, 2011 |
| Agriculture value | Agricultural crop[1] output values in lakh rupees, averaged from 2002 through 2005, per capita | Indian Ministry of Statistics and Programme Implementation's Database |
| Urban quality of life | A calculated urban version of the Human Development Index, from 2005 | Meghalaya Planning Department's Human Development Report 2008 |
| Fishing value | Fishing (marine and inland) output values in lakh rupees, averaged from 2002 through 2005 per area[2] | Indian Ministry of Statistics and Programme Implementation Database |
| Poverty benefits | The number of households per capita in 2009 that received benefits under a social welfare scheme called the National Rural Employment Guarantee Act, which entitles a member of rural households to 100 days of low-paid temp work in publicly assigned projects and jobs. | Indian Ministry of Rural Development's Implementation Report Under NREGA |
| Marginalized caste | Percent of the population officially "scheduled" as low caste, or socially/religiously marginalized and "backward" in 2001 | Indian Ministry of Home Affairs' Office of the Registrar General, Census 2001 |
| Population density | An average of person per square kilometer figures from the 2001 and 2011 censuses. | Indian Ministry of Home Affairs' Office of the Registrar General, Census 2001, 2011 |

The population under investigation includes all 28 Indian states and one centrally administered union territory.[3] India's remaining six union territories were excluded in an effort to remove outliers with small amounts of forest cover. The reasoning for this exclusion: Even small absolute

[1] Agriculture value in this paper specifically looks at crop values. Initial research found strong correlations between values of livestock output and forest cover change as well.
[2] The per area calculation was significantly correlated with forest cover growth, where as a per capita calculation was not.
[3] In addition to all 28 Indian states, the one union territory included in the analysis is the territory of the Andaman and Nicobar Islands, an archipelago of more than 500 islands in the Bay of Bengal that behaves, statistically, like many states and has a substantial amount of forest cover.

changes in states with little overall forest cover could register as substantial growth in a percent change calculation, potentially skewing the analysis. Of the excluded territories, the highest amount of forest cover is found in Dadra and Nagar Haveli, which had 219 square kilometers of forest cover in 2000. By comparison, Haryana, with 1,754 square kilometers of forest cover that year, represented the lower bound for inclusion.

At this point, it's worth mentioning a word about calculations of forest cover in India. Forest resources carry the legacy of colonial times when bureaucrats and forestry scientists governed forests. Local people were, for the most part, officially barred from owning or accessing forestland without permission, though they may have done so routinely in practice. After Independence, this style of management continued into the present; though forests represented livelihoods for many and sacred spaces for some, they were on paper the domain of state governments. There are notable exceptions where communities have taken charge of forest resources for decades, but forests largely remain the property of — and demarcated by — the state.

This analysis relies on forest cover assessments published by the Forest Survey of India in its (mostly) biennial State of Forest Report (SFR). These reports rely on satellite data that are processed digitally with human involvement in correction, estimation and validation through on-the-ground research. This, however, does lead to a discrepancy between SFR forest cover totals and officially designated forestland. Official designations of forests rarely change; land once declared forest may remain forest on paper despite having few if any trees. That becomes clear when analyzing differences between official recorded forest and satellite determined forest cover. Some states have more forest cover than officially recorded forest areas; others, substantially less.

Forest cover estimates from the 2001 SFR refer mostly to satellite data taken from the end 2000 (though in the case of Madhya Pradesh and Maharashtra, they refer to 1998). The SFR 2011 report covers imagery taken from October 2008 to March 2009. The SFR reports define forest cover as any area with at least a 10 percent tree canopy. Methods are periodically refined over time, leading to slight adjustments in any given biennial report — some states gain, some states lose. As figures for older years are not routinely revised, this paper ignores those effects.

## METHOD AND FINDINGS

As previously indicated, data on a wide number of variables were collected to test various hypotheses from academic literature. Through a process of elimination, the final six independent variables were chosen.[4] The paper will now begin with a univariate analysis of basic descriptive statistics. This is followed by a scatterplot of the dependent variable vs. the hypothesized key independent variable as well as a table of bivariate correlations. Finally, the paper models several combinations of variables for different effects through OLS regression.

*Univariate analysis*

Table 2 presents basic descriptive statistics – number of observations with valid data as well as minimum, maximum and standard deviation – for all variables considered in this analysis.

[4] See Appendix I for more information.

**Table 2 — Descriptive statistics of key variables predicting variation in forest cover**

| | N | Min. | Max. | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Forest cover change (%) | 29 | –27.467 | 21.528 | 2.981 | 8.934 |
| Agriculture value (lakh rupees per capita) | 29 | .019 | .101 | .044 | .016 |
| Urban quality of life (urban HDI score) | 29 | .618 | .877 | .757 | .072 |
| Fishing value (lakh rupees per area) | 29 | .010 | 9.670 | 1.360 | 2.369 |
| Poverty benefits (# of households per capita participating) | 29 | .005 | .182 | .069 | .050 |
| marginalized caste (%) | 26 | .500 | 28.900 | 13.231 | 7.646 |
| Population density (persons per square kilometer) | 29 | 15.000 | 991.000 | 328.862 | 270.270 |

In the dependent variable measuring forest cover percent change between 2000 and 2009, we can see mean positive growth, a fact that has been heralded by Indian policy makers as a victory. However, there is substantial variance as the standard deviation (8.934) is nearly three times the mean. Values range from a decrease of 27.467 percent in the Punjab to an increase of 21.528 in West Bengal. These observations are the most extreme values remaining after six territories were already cast aside as outliers. It's worth noting that even if West Bengal and the Punjab were removed, the main bivariate correlation (see below) remains significant.

Fishing values per area are the other remaining variable with substantial variation, with a standard deviation (2.369) that is 1.7 times the variable mean. Obviously, fishing requires a body of water or access to the ocean, so it is not surprising then that states with coastline correlate with fishing value. The state of West Bengal on the east coast demonstrates the highest (9.670 lakh rupees per square mile). That said, it should also be noted that several inland states still record higher fishing output per area than other states with coastline.

Agriculture value per capita has low variation with a standard deviation slightly more than one-third (.016) of the variable mean. Low variation demonstrates that all states rely on agriculture to some degree. Nationally, agriculture made up almost 19 percent of GDP in 2004; the sector directly employs roughly half of the country's workforce.

Urban quality of life, based on an urban Human Development Index calculation, varies little with a standard deviation (.072) that is less than one-tenth the variable mean. The minimum urban quality of life (.618) occurs in Uttar Pradesh, India's most populous state. The maximum (.877) is found in the northeastern state of Arunachal Pradesh.

The numbers of households receiving poverty benefits per capita has a standard deviation (.050) that is 70 percent of the variable mean, representing low variation. It's worth noting that few households receive benefits relative to population. Though it's tempting to consider this a measure of abject poverty, the numbers also represent the government's ability to provide — and the existence of — economic opportunities. Mizoram records the maximum. Goa, a wealthier Western coastal state, records the minimum.

The standard deviations of percent marginalized caste (7.646) is 57 percent of the variable mean. The range varies from a little as half a percent of the population considered a marginalized caste in Meghalaya to a high of 28.9 percent in the Punjab. The variable has only 26 observations as values are missing for the Andaman and Nicobar Islands, Mizoram and Nagaland as they either don't officially recognize low castes or they have not calculated such a number.

Population density's standard deviation (270.270) is 82 percent of the variable mean. Worth noting, the initial remover of outliers also excluded hyper-dense city-states of Delhi and Chandigarh. The maximum population density of the states and territories studied is the impoverished east-central state of Bihar. The lowest density is found in Arunachal Pradesh.

As an aside, there are a number of statistically significant correlations between the variables considered in this analysis and a regional binary variable created for the eight northeastern states (Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim and Tripura).[5] These states are rural, somewhat mountainous and isolated from the remainder of the Indian mainland. It's not surprising to see a regional effect, however, there is not regional correlation with forest cover so the variable was removed from ultimate consideration.

*Bivariate analysis*

A scatterplot of the dependent variable of forest cover change against agriculture crop output values per capita demonstrates a clear, inverse relationship. As noted in Figure 1, the $R^2$ value shows that 39.8 percent of the variation in forest cover change is explained by agriculture value. This is certainly powered some by the Punjab, which records both the highest per capita agriculture value — it is, indeed, the most intensively agrarian state in India and often referred to as the breadbasket of the country — as well as the highest forest cover loss. It's worth noting that even if this observation were removed, the correlation holds significance. Though no statistical analysis can prove causation, the correlation remains compelling.

[5] See Appendix II for more information

**Figure 1 — Scatterplot of relationship between forest cover change and agriculture value**

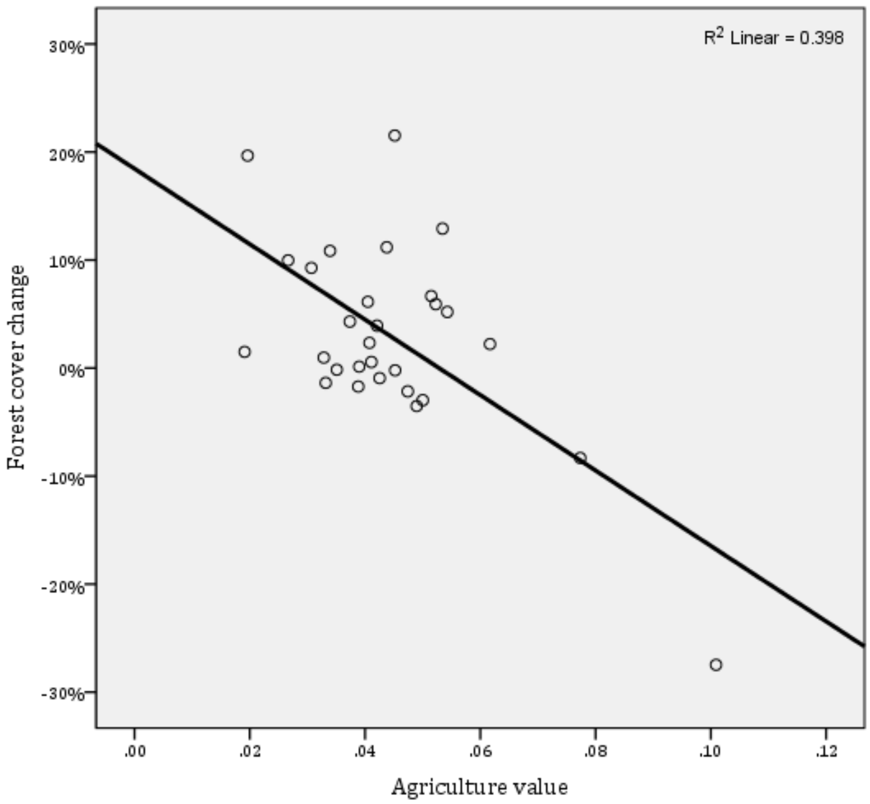


Table 3 shows Pearson's r-values for the dependent variable as well as the six independent variables under consideration in this analysis. Variables are marked according to the level of their statistical significance. All variables, except the marginalized caste percentage, have 29 recorded observations. Marginalized caste, as explained above, has 26.

**Table 3 — Correlation matrix of key variables predicting variation in forest cover**

| | Forest cover change | Ag. value | Urban quality of life | Fishing value | Poverty benefits | % margin. caste | Pop. density |
|---|---|---|---|---|---|---|---|
| Forest cover change | 1 | | | | | | |
| Agriculture value | −0.631** | 1 | | | | | |
| Urban quality of life | −0.016 | 0.261 | 1 | | | | |
| Fishing value | 0.434* | 0.028 | 0.146 | 1 | | | |
| Poverty benefits | 0.198 | −0.317 | 0.206 | −0.290 | 1 | | |
| % margin. caste | −0.202 | 0.386† | −0.313 | 0.013 | −0.195 | 1 | |
| Pop. density | 0.339† | −0.007 | −0.365† | 0.563** | −0.461* | 0.428* | 1 |

** = significant at the .01 level (2-tailed)
* = significant at the .05 level (2-tailed)
†= significant at the .1 level (2-tailed)

Agriculture value remains the strongest, with a Pearson's r-value of –.631, a strong negative correlation with forest cover change. This value is significant at the .01 level. This result is supported by literature on deforestation: Simply put, agriculture and forests are two competing uses for land. I and others interpret this to suggest that as the value of agriculture rises, more pressure exists to convert standing trees into cropland.

Fishing output value per area meanwhile is positively associated with forest cover change, a correlation that is significant at the .05 level. I suggest this may have to do with a state's employment diversity. A vibrant fishing industry that produces higher output levels generates income and employment that reduces the pressure to resort to deforesting activities, including agriculture.[6]

Population density correlates positively with forest cover change but only at the .1 level. Some scholars have suggested that increasing population density may lead to increasing agricultural intensity, as opposed to cropland expansion. This could mean that denser populations represent consolidated farming at industrial scales, relieving pressure to expand forests; farmers instead focus on getting more out of their land. This theory finds some support in literature suggesting that increasing numbers of rural poor put pressure on forest land margins. Notable however in this analysis: Population density shows no correlation with agriculture output values. It is strongly, significantly and positively correlated with fishing values. Though it might be initially tempting to suggest that population density could naturally lead to more concentrated urban populations that are less involved in deforestation, no bivariate correlation between urban population percentages and forest was found in an initial weed-out of variables. Population density's other correlations with poverty benefits and marginalized caste percentages will matter in the context of a multivariate regression below. The complex ways in which population density appears to interact with various variables suggests a need for further study.

Poverty benefits and marginalized caste percent do not correlate significantly with forest cover change. A multivariate, ordinary least squares regression analysis will explore the ways in which they interact with forest cover further below.

*Multivariate analysis*

Table 4 shows a series of models combining independent variables in different steps into an ordinary least squares regression. Due to the limited number of observations, no more than three independent variables were included in any one model. The purpose of presenting several different models is then to simply demonstrate the importance of different variables, and in some cases tease out significance. Of particular interest here are the varying calculations of Adjusted $R^2$ as a percentage of model fit.

This multi-model analysis considers the effects of agricultural output values along with urban quality of life, fishing output, poverty benefits and a marginalized caste percentage. When introduced, population density is clearly a factor as well, though in these regressions it is used as a control to bring out significance in other variables — namely urban quality of life, poverty benefits and caste percentage. I suggest this result demonstrates the complex ways in which population density might interact with the dependent variable.

The key takeaway from this analysis: It is difficult to overstate the relationship in this time period that agriculture has with deforestation. In the bivariate analysis above, agriculture value had a strong negative association that continues to be demonstrated in the multivariate regression. For comparison sake, an Adjusted $R^2$ calculation for agricultural value alone regression (not modeled below) is 37.6 percent, which dips slightly from the bivariate non-adjusted $R^2$ of 39.8 percent.

[6] Though the data was unavailable for this analysis, follow-up research might consider alternative variables along the lines of my hypothesis, looking at both tax receipts and employment percentage by sector. I'm suggesting that in states where more people are employed in non-agricultural activities, forests would face less pressure.

**Table 4 — Predictors of variation in forest cover from 2000 to 2009**

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| **LIVELIHOOD/ OPPORTUNITY** | | | | | | |
| Agriculture value | –.629 (.000)** | –.716 (.000)** | –.644 (.000)** | | | |
| Urban quality of life | | .338 (.025)* | | | | |
| Fishing value | | | .452 (.001)** | .537 (.004)** | | |
| Poverty benefits | | | | .354 (.049)* | .411 (.031)* | |
| % margin. caste | | | | | –.424 (.028)* | –.433 (.037)* |
| **CONTROL** | | | | | | |
| Population density | .334 (.022)* | .457 (.003)** | a | a | .708 (.001)** | .541 (.011)* |
| N | 29 | 29 | 29 | 29 | 26 | 26 |
| Adjusted $R^2$ % | 47.2% | 55.3% | 57.2% | 24.9% | 34.1% | 21.7% |

a = variable not included due to multicolinearity
** = significant at the .01 level.
* = significant at the .05 level
Significance in parentheses.

In Model 1, when controlling for the effect of population density, agriculture value's negative association remains almost unchanged in strength and significance. Meanwhile, controlling for agriculture's powerful effect, population density becomes significant at the .05 level and the variable displays a positive, moderately strong relationship with forest cover change. Adjusted $R^2$ gains almost 10 percentage points to 47.2 percent.

In Model 2, urban quality of life is added — and is significant at the .05 level — and model fit jumps to 55.3 percent. Urban quality of life, controlling for the other variables, is positively associated with forest cover change, supporting my hypothesis that increasing incentives for urban living are associated with positive forest growth. This significance at the .05 level is missing in a bivariate analysis. Population density remains significant and gains strength its positive association with forest cover. Controlling for the positive effects of other variables, agriculture value's negative association only strengthens to a starkly pronounced –.716, suggesting that dispersed rural, agrarian life is indeed a strong driver of deforestation.

Model 3 represents the best fit of those tested with 57.2 percent. Controlling for agriculture, fishing value becomes significant at the .01 level (rather than only at the .05 in a bivariate analysis) and is positively associated with forest cover change. Agriculture remains strongly and negatively associated with forest cover change. This appears to support my hypothesis that increasing fishing value — as it represents a viable alternative to agriculture — indeed relieves pressure from forests.

Model 4 purposefully removes agriculture value from the regression to look at other variables. Not surprisingly, model fit drops to only 24.9 percent, again demonstrating the significant pressure that agriculture puts on forests. Fishing value remains significant with a strong positive relationship to forest cover change. Meanwhile, poverty benefits, when controlling for fishing value, become significant at the .05 level with a moderate positive relationship. These two positive effects reinforce my argument that alternatives to agriculture may alleviate demand to convert forestland.

Both Models 3 and 4 remove population density as an independent variable to due its colinearity with fishing value. When this variable is included, Adjusted $R^2$ rises suspiciously and yet significance of drops.

In Model 5, Adjusted $R^2$ rises to 34.1 percent, higher than model 4 but still substantially lower than when agriculture value is included in the regression. The positive relationship between poverty benefits and forest cover change strengthens somewhat, when controlling both for population density and percent marginalized caste. Population density's significant association with forest cover change also strengthens dramatically.

However, most notable in Model 5 model is the significant, negative association between the percent of a population that is low caste and forest cover change, when controlling for the other variables. I suggest that this negative relationship emphasizes the pernicious effect of caste marginalization: higher numbers of low caste are likely correspond to a lack of economic opportunity and mobility, which may keep people locked in dependence on forest degrading activity. In this view, it's not surprising that the Punjab, the most agrarian state, also has the highest percentage of low caste citizens. This may reflect inequity in the Punjab, as it nonetheless also has above average GDP per capita figures of Indian states in this analysis. This also may shed light on a positive correlation, observed only the .1 significance level, between the percentage of marginalized caste and agriculture value.

In Model 6, removing poverty benefits does cause Adjusted $R^2$ to drop substantially; this model fits worst of those considered at only 21.7 percent. Population density's positive association remains though significance drops slightly to the .05 level. The effect of caste marginalization strengthens with the removal of controls for poverty benefits.

In interpreting Models 5 and 6, it might be tempting to conclude that this analysis supports the body of scholarship that suggests poverty is a driving factor behind environmental degradation. I do suggest that desperation and a lack of economic opportunity as part of the equation, it should be noted that GDP per capita — another measure of poverty — demonstrated no significant correlation with forest cover change, nor did it demonstrate any significance in a number of variable combinations in initial test regressions and therefore was removed from ultimate consideration. In the Indian context in this period, it seems that higher GDP simply doesn't interact in a clear way with forest cover growth.

## CONCLUSION

In conducting this research I set out to investigate a complex question: What explains variation in forest cover change across Indian states between 2000 and 2009. I hypothesized that agriculture would likely be a key driver, but I additionally suggested that the presence of alternative lifestyles and livelihoods would be mitigating factors. Starting with a lengthy list of variables, I eventually paired down my analysis to six independent variables: agriculture crop value per capita, urban quality of life, fishing out value per area, households per capita receiving poverty benefits, the percentage of marginalized caste individuals and population density.

First and foremost, my analysis strongly supports a body of academic literature that suggests agriculture value indeed is negatively associated with forest cover change. Models including the impacts of agriculture value record Adjust $R^2$ percentages from 47.2 to 57.2 percent. This is not surprising as India is an agrarian nation and farming pervades the lives of a majority of the population.

That said, I also find statistical support for my secondary hypothesis that forest cover change is positively associated with the existence of alternative livelihoods and incentives for alternative lifestyles. I am, in essence, making a claim about the benefits of diversity in an economy. We see that higher urban quality of life — representing a potential lure of people away from agriculture — as well as higher values of fishing output and higher participation in a government poverty/unemployment scheme all display a positive relationships with forest cover change. At the same time, increasing percentages of low caste individuals — people who are often socially and economically limited in mobility — seem to be associated negatively with forest cover growth. This seems to suggest a particularly pernicious dependence on forest degrading activities.

The effect of population density also appears to be positive on forest cover growth; there may be many reasons for this and I hesitate to make strong claims — particularly as the literature is divided — for exactly why population density appears to coincide with forest expansion. There may be something that resembles an economy of agglomeration effect — as populations become denser, more and varied employment opportunities arise, some of which remove pressure from the forest. Ultimately, however, such a claim is beyond the central analysis of the paper.

*Limitations*

Ultimately, it must be noted that the small number of studied states is a limiting factor in this statistical analysis. Though this study has the advantage of being able to spot trends and relationships in country specific variables and in the context of a particular nation's history, attitudes and culture, the downside of a small study population remains: trends are subject to greater influence by exemplar cases. Follow-up study would benefit from expanding the analysis from the state level down to the district level, thereby greatly increasing the number of observations across all states.

## Appendix I – Tested but excluded variables

Variables considered were in many cases averaged over multiple years, when data were available. Exclusions were made based on extreme outliers, missing observations and, in most cases, lack of significant bivariate correlation with the dependent variable.

**General**

Forest cover, forest cover as a percentage of area, area, regional binary variables (northeast, north, east, west, south, coastal)

**Agricultural**

pastureland as a percentage of area, change in pastureland, sown land as a percentage of area, change in sown land, cattle per capita, buffaloes per capita, sheep per capita, goats per capita, poultry per capita,

**Political/policy**

environmental sustainability index, panchayats, rural population per panchayat, forest area relative to number of panchayats, number of local panchayat reps, female representation per panchayat, low caste representation per panchayat, tribal representation per panchayat, households seeking NREGA benefits per capita, percent of NREGA demands met, voter turnout, candidates per Lok Sabha seat,

**Forest governance**

officially demarcated forest land, percent of official forest denoted Reserved, percent of official forest denoted as Protected, percent of official forest denoted as Unclassified, observed forest cover as a percent of officially denoted forestland, percent of land protected as a park or sanctuary, land under joint forest management relative to observed forest, land under joint forest management (JFM) relative to official forest, number of JFM institutions, number of JFM institutions per capita, JFM area per JFM institution, observed forest area relative to number of JFM institutions, environmental aid per capita, environmental aid per forest area, projected government forestry spending needed per forest area, actual government forestry spending per forest area, actual government forestry spending as a percent of projected need, projected government ecology spending needed per forest area, actual government ecology spending per forest area, actual government ecology spending as a percent of projected need, illegal logging per forest area

**Non-Agricultural Economic**

coal output value per capita, coal output value per area, coal output value per observed forest, mining output value per capita, mining output value per area, mining output value per observed forest, agriculture output value per area, agriculture output value per sown land, agriculture output value per observed forest, livestock output value per capita, livestock output value per area, livestock output value per observed forest, non-timber forest product output value per capita, non-timber forest product output value per area, non-timber forest product output value per observed forest, timber output value per capita, timber output value per area, timber output value per observed forest, charcoal output value per capita, charcoal output value per area, charcoal output value per observed forest, fishing output value per capita, fishing output value per observed forest, GDP per capita, foreign direct investment per capita, GDP growth, percent formal employment in central government, percent formal employment in state government, percent formal employment in quasi central government, percent formal employment in quasi state government, percent formal employment in local government, percent formal employment in all levels of government, percent formal employment in small private sector, percent formal employment in large private sector, percent formal employment in private sector, percent population in formal employment,

**Demographic/social**

population, population per forest area, population change, percent of the population that is rural, rural population per forest area, rural population chance, change in population density, females per thousand males, female literacy, rural GINI coefficient, urban GINI coefficient, percent of population declared "tribal," percent of population that is Hindu, percent of population that is Sikh, percent of population that is Muslim, percent of population that is Christian, percent of population that is Buddhist, percent of population that is Jain, percent of population that follows another religion, percent of women who read a newspaper, percent of women who watch TV, percent of women who believe husbands are justified in abusing their wives,

**Development**

per capita power consumption, total roads, surfaced roads, cars per capita, rural HDI, HDI,

**Appendix II –**

Binary variables were created for all regions of India. Though not bearing directly on the dependent variable studied in this paper, it's worth noting that two key independent variables for forest cover change demonstrate correlations — detailed below — with the binary variable for India's Northeast region.

**Table 3 — Correlation matrix of key variables predicting variation in forest cover**

| | Northeast | Urban quality of life | Poverty benefits | % margin. caste | Pop. Density |
|---|---|---|---|---|---|
| Northeast | 1 | | | | |
| Urban quality of life | .383* | 1 | | | |
| Poverty benefits | .731** | .206 | 1 | | |
| % margin. caste | –.562** | –.313 | –.195 | 1 | |
| Population Density | -.419* | –.365† | –.461* | .428* | 1 |

** = significant at the .01 level (2-tailed
* = significant at the 0.05 level (2-tailed)
†= significant at the 0.1 level (2-tailed)