Vyāghranomics in Space and Time

Estimating Habitat Threats for Bengal, Indochinese, Malayan and Sumatran Tigers

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Abstract

As the wild tiger population in tropical Asia dropped from about 100,000 to 3,500 in the last century, the need to conserve tiger habitats poses a challenge for the Global Tiger Recovery Program. This paper develops and uses a high-resolution monthly forest clearing database for 74 tiger habitat areas in ten countries to investigate habitat threats for Bengal, Indochinese, Malayan and Sumatran tigers. The econometric model links forest habitat loss and forest clearing to profitability calculations that are affected by market expectations, environmental conditions and evolving patterns of settlement, among others. It uses new spatial panel estimation methods that allow for temporal and spatial autocorrelation. The econometric results emphasize the role of short-

run market variables, including the exchange rate, real interest rate and prices of agricultural products in forest clearing, with considerable variation in the estimated timing for response and impact elasticities across countries. The results highlight a critical message for the conservation policy community: Changes in world agricultural-product markets and national financial policies have significant, measurable effects on tropical forest clearing, with variable time lags and degrees of responsiveness across countries. Measuring these effects and pinpointing areas at risk can provide valuable guidance for policymakers, conservation managers, and donor institutions.

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***Vyāghranomics* in Space and Time: Estimating Habitat Threats for Bengal, Indochinese, Malayan and Sumatran Tigers.**

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1. Introduction

During the past century, the wild tiger population of tropical Asia has plummeted from an estimated 100,000 to around 3,500. Table 1 summarizes current estimates of surviving populations for the four tropical-forest subspecies: Bengal (2,376 remaining), Indochinese (342), Malayan (500) and Sumatran (325).¹ As Figure 1 shows, their remaining habitat forms a scattered arc from southwest India to northwest Indonesia, much of it in upland areas. Bengal tigers survive in India, Nepal, Bhutan, Bangladesh and northern Myanmar, while the remaining Indochinese tigers are found in western Myanmar², Lao PDR, Vietnam, Cambodia and Thailand. In contrasting geographic concentration, Sumatran tigers are confined to one Indonesian island and Malayan tigers exist only in Peninsular Malaysia and one small area in southern Thailand.

Table 1: Surviving Wild Tiger Populations*

<u>Bengal^a</u>		<u>Indochinese^d</u>		<u>Malayan^e</u>		<u>Sumatran^g</u>	
India	1,706 ^b	Thailand	200 ^c	Malaysia	500 ^f	Indonesia	325 ^c
Bangladesh	440 ^c	Myanmar	85 ^c	(Peninsular)		(Sumatra)	
Nepal	155 ^c	Vietnam	20 ^c				
Bhutan	75 ^c	Cambodia	20 ^c				
		Lao PDR	17 ^c				
Total	2,376		342		500		325

* Midrange estimates

^a No current estimate for Myanmar

^b Source: Jhala, et al. (2011)

^c Source: GTRP (2010)

^d See Lynam and Nowell (2011)

^e See Kawanishi and Lynam (2008)

^f Source: GTRP (2010); no current estimate for southern Thailand

^g See Linkie, et al. (2008)

The global community has mobilized to conserve the tiger's remaining habitat through the Global Tiger Initiative, which is supported by all countries with known tiger populations, the

Figure 1: Tiger Subspecies Landscapes and Elevation*

¹ The South China tiger is believed to be extinct in the wild; the Amur Tiger's range is confined to the Russian Far East and the contiguous border region of China (and perhaps North Korea).

² The ranges of the Bengal and Indochinese tigers may overlap in Myanmar; Figure 1 provides an approximation.

* Estimated surviving tigers in parentheses.

Sources: WWF (2010) GTRP (2010); Chundawat, et al. (2011); Jhala, et al. (2011); Kawanishi and Lynam (2008); Linkie, et al. (2008); Lynam and Nowell (2011)

World Bank, and over 40 civil society organizations.³ In November 2010, heads of state and high-level representatives from all 13 tiger range countries attended the world's first tiger summit, convened in Moscow by the presidents of Russia and the World Bank. All participating countries endorsed the Global Tiger Recovery Program, which aims to double the number of tigers by 2022 through habitat conservation programs and cooperation across national boundaries to stop poaching and illegal trade in tiger parts.⁴

The Global Tiger Initiative confronts numerous challenges, including the need to conserve habitats large enough to support breeding populations; varied threats to the four tropical subspecies; divided national jurisdictions; differences in countries' institutional capabilities and willingness to pay for conservation; and, not least, pervasive opportunities for profitable conversion of remaining habitat areas (Damania, et al. 2008)⁵. In light of these opportunities, the tropical GTI countries' interest in preserving tiger habitat has undoubtedly been enhanced by REDD+ (Reduced Emissions from Forest Destruction and Degradation)⁶, whose programs provide compensation for forest conservation. At present, 9 tiger range countries have formally joined the REDD+ partnership⁷: Cambodia, China, India, Indonesia, Lao PDR, Malaysia, Nepal, Thailand and Vietnam. Documented preparation for REDD+ programs is underway in the following tiger range countries: [Bangladesh](#), [Bhutan](#), [Cambodia](#), [Indonesia](#), [Lao PDR](#), [Myanmar](#), [Nepal](#), [Thailand](#) and [Vietnam](#) (references hyperlinked).

REDD+ recognizes that habitat conservation is primarily a development problem, because natural forests in poor regions are very costly to protect without the active support of

³ For more complete information, see <http://www.globaltigerinitiative.org/html/participants.php>

⁴ This paper focuses on forest habitat loss, but we recognize that poaching and illegal trade in tiger parts can devastate remaining tiger populations, even when forest habitat is intact.

⁵ Another challenge for the GTI will be sustaining the momentum provided by World Bank leadership during the startup period.

⁶ See <http://www.un-redd.org/AboutREDD/tabid/582/Default.aspx>

⁷ See <http://reddpluspartnership.org/73857/en/>

neighboring communities (Chomitz et al. 2006; Kaimowitz and Angelsen 1998). This is a core issue for the Global Tiger Initiative (GTI), which must allocate its resources effectively while confronting a short time horizon (to prevent tiger subspecies extinctions), a complex, constantly-changing spatial distribution of potential conservation benefits and costs, and the risk of rapid, irreversible losses in areas where conservation is weak. Locally-tailored GTI solutions will undoubtedly include REDD+ conservation payments; targeted monitoring and enforcement of conservation regulations where threats are urgent; and enlistment of critical local and national institutions.

To support cost-effective solutions, our research project is developing a spatially-referenced empirical model that can identify critical habitat areas for potential GTI programs. Identification of such areas is not a static problem, because tropical forest clearing constantly evolves in response to changing economic and environmental conditions. This paper describes the first stage of the project, which has developed two supporting resources:

- (1) A frequently-updated, high-resolution database for tracking threats to remaining tiger habitat in 11 tropical forest countries: Bangladesh, Bhutan, Cambodia, India, Indonesia, Lao PDR, Malaysia, Myanmar, Nepal, Thailand and Vietnam.
- (2) Country-specific spatial econometric models that identify critical drivers of forest habitat destruction.

The remainder of the paper is organized as follows. Section 2 develops a model of forest clearing that highlights economic determinants. Section 3 introduces the most critical input to our analysis: FORMA (Forest Monitoring for Action), a new high-resolution database that permits near-real-time assessment of forest habitat conditions in the tropical tiger range countries. In Section 3, we develop a spatial formatting protocol for our database that is based on critical minimum tiger habitat size. We use this protocol to integrate the FORMA data with spatially-referenced information on remaining forest habitat, currently-protected areas, and

potential determinants of forest clearing identified by the modeling exercise in Section 2. Section 4 illustrates our database with an assessment of habitat threats in central Sumatra. In Section 5, we estimate econometric models of forest clearing in 10 tiger range countries using newly-available spatial panel techniques. Section 6 discusses our econometric results, while Section 7 summarizes and concludes the paper.

2. Model Specification

2.1 Previous Research

Previous empirical research has assessed the relative importance of numerous factors that may influence the conversion value of forested land. These include local population scale and density, distance from markets, the quality of transport infrastructure, agricultural input prices, physical factors such as topography, precipitation and soil quality, and zoning into categories that include protected areas. The results are generally consistent with a model in which the conversion of forest land varies with potential profitability.

Nelson and Chomitz (2009) and Rudel, et al. (2009) have studied land-use change across countries over multi-year intervals. Within counties, numerous econometric studies have estimated the impact of drivers across local areas during multi-year intervals. Some studies have used aggregate data for states, provinces or sub-provinces (e.g. studies for Brazilian municipios by Pfaff (1997) and Igliori (2006), and Mexican states by Barbier and Burgess (1996)). Many studies have also used GIS-based techniques to obtain multi-year estimates at a higher level of spatial disaggregation (e.g., Cropper, et. al. (1999, 2001) for Thailand; Agwaral, et al. (2002) for Madagascar; Deininger and Minton (1999, 2002), Chowdhury (2006) and Vance and Geoghegan (2002) for Mexico; Kaimowitz, et al. (2002) for Bolivia; and De Pinto and Nelson (2009) for Panama). In rarer cases, studies have used annual national or regional aggregate time series over

extended periods (e.g., Zikri (2009) for Indonesia; Ewers, et al. (2008) for Brazil). These studies are hindered by limited degrees of freedom, since they must control for many factors, observations are annual at best, and the possibility of interim structural change leads to questions about the stability of estimated model parameters.

While econometric work on long-run forest clearing drivers is well-advanced, data problems have limited most treatments of economic dynamics to theoretical work and simulation modeling. Arcanda, et al. (2008) and others have studied the theoretical relationships between macroeconomic drivers and forest clearing. Notable simulation exercises include Cattaneo (2001) for Brazil and San, et al. (2000) for Indonesia. In the first application of the FORMA data, Wheeler et al. (2011) have investigated the impact of market, environmental and demographic variables on forest clearing in the Indonesian archipelago.

Among studies that test the effect of protective zoning on forest clearing, Nelson and Chomitz (2009) provide the most rigorous and comprehensive assessment. They find that protected areas have less land clearing, *ceteris paribus*, which supports the specific results of Gaveau, et al. (2009) for Indonesian Sumatra.

2.2 Model Specification

Drawing on these studies, we posit that the profitability of deforesting an area in a subregion of a particular country is determined by a large set of economic, demographic and environmental factors:

$$(1) \pi_{it}^e = \pi_{it}^e(p_i^e, t_i, i_i^e, y_i, l_i, x_i^e, w_{it}, e_i, n_i, r_i)$$

$$H_0: \pi'(p^e) > 0, \pi'(t) < 0, \pi'(i^e) < 0, \pi'(y) ? 0, \pi'(l) < 0, \pi'(x^e) > 0, \pi'(w) < 0, \pi'(e) < 0, \pi'(n) ? 0, \pi'(r) < 0$$

π	=	Expected profitability of deforesting area i, time t
p^e	=	Vector of expected prices for relevant products
t	=	Transport cost per unit of output
i^e	=	Expected interest rate
y	=	Income per capita
l	=	Land cost
x^e	=	Expected exchange rate (local currency/dollar)
w	=	Precipitation
e	=	Elevation
n	=	Population density
r	=	Level of enforced forest protection

In this specification, the expected profitability of deforesting an area increases with expected revenue from production on cleared land, which in turn depends on the expected prices of feasible products. Expected profitability declines with increases in the unit costs of transport, capital, low-skill labor and land. Transport costs are positively related to the distance to relevant markets, as well as the proximity and quality of local roads. The real interest rate provides a reasonable proxy for the unit cost of capital. In the case of low-skill wages, an ambiguity is introduced by the available proxy, local income per capita, whose potential impact on profitability incorporates at least three partial effects as income increases: negative, via low-skill wages (on the assumption that low-skill wages reflect average incomes because income distributions have rough parity across relevant areas in the same country); negative, via income-related willingness and ability to pay for establishing, monitoring and enforcing local forest protection measures; and positive, via increased demand for local forest products and land for commercial and residential development.

Commodities that can be produced on cleared tropical forest land are tradable on international markets (e.g., palm oil, lumber, rubber, tropical fruits and vegetables). The

expected profitability of deforesting an area varies directly with the exchange rate, since dollar-denominated input costs fall as the exchange rate rises (and conversely). We posit effects for local structural factors as well. Forest clearing is more costly in areas (and months) with heavier precipitation, and the productivity of tropical plantation crops (e.g., palm oil) declines with elevation. Higher population density should increase the demand for cleared land, *ceteris paribus*, but the overall effect of population density is ambiguous *a priori*, because it may also proxy the extent of previous clearing in an area. The partial effect of density will be negative in the latter dimension, because new opportunities for large scale clearing will be more limited.

Equation (2) describes the basic dynamics of deforestation in our model.⁸ In this specification, the rate of change in forest clearing in period t is a function of the gap between actual deforestation and steady-state deforestation, which is determined by expected profitability.

$$(2) \quad \dot{f}_{it} = \theta(\ln F_{it}^*(\pi_{it}^e) - \ln F_{it})$$

where, for area i , period t :

$$\begin{aligned} F_{it}^* &= \text{Steady-state deforestation} \\ F_{it} &= \text{Current deforestation} \end{aligned}$$

Using a first-order logarithmic approximation of the change rate for estimation, we obtain:

$$(3) \quad \ln F_{it} - \ln F_{it-1} = \theta(\ln F_{it}^*(\pi_{it}^e) - \ln F_{it-1})$$

Re-arranging:

$$(4) \quad \ln F_{it} = (1 - \theta) \ln F_{it-1} + \theta \ln F_{it}^*(\pi_{it}^e)$$

⁸ In the logistic specification of (2), the rate of change is a function of the gap between steady-state and current values of change determinants. In the Gompertz specification, the rate of change is a function of the gap between log-values. We employ the Gompertz specification because it provides a better fit to the data in many applied cases, and because it supports a log-specification of model determinants which is a first-order approximation to an arbitrarily-specified profit function. We believe that this is preferable to the linear specification, which incorporates the implausible assumption of infinite substitution elasticity among profitability determinants. For further discussion of the Gompertz specification and its application, see Chow (1983).

Steady-state deforestation in equation (2) is driven by expected profitability, whose determinants are specified in equation (1). Specifying a log-linear relationship between F^* and the determinants of profitability, we obtain the following equation:⁹

$$(5) \ln F_{it}^* = \beta_0 + \sum_{k=0}^n \delta_k \ln p_{t-k} + \beta_1 \ln t_i + \sum_{j=0}^n \gamma_j i_{t-j} + \beta_2 \ln y_i + \beta_3 \ln l_i + \sum_{l=0}^n \phi_l x_{t-l} + \beta_4 \ln w_{it} + \beta_5 \ln e_i + \beta_6 \ln n_i + \beta_7 r_i$$

From (4) and (5) we obtain the estimating equation in (6). We incorporate explicit lags to account for expectations formation for the interest rate, international market prices (we use one variable to represent the set) and the exchange rate.

$$(6) \ln F_{it} = (1 - \theta) \ln F_{it-1} + \theta(\beta_0 + \sum_{k=0}^n \delta_k \ln p_{t-k} + \beta_1 \ln t_i + \sum_{j=0}^n \gamma_j i_{t-j} + \beta_2 \ln y_i + \beta_3 \ln l_i + \sum_{l=0}^n \phi_l x_{t-l} + \beta_4 \ln w_{it} + \beta_5 \ln e_i + \beta_6 \ln n_i + \beta_7 r_i) + u_{it}$$

In this model, u_{it} is a stochastic error term with exogenous components that are both spatially and temporally correlated. We discuss estimation strategy in Section 5.

In summary, equation (6) links deforestation (henceforth forest clearing) to profitability calculations that are affected by market expectations, environmental conditions, and evolving patterns of settlement, economic activity, infrastructure provision and regulatory activity. In each month, the evolution of clearing in response to these factors is perturbed by two types of stochastic shocks: Local rainfall, and market-induced revision of expectations about future levels of the exchange rate, the real interest rate, and the prices of agricultural commodities that could be produced if the forested land were cleared. Full adjustment to these changing factors is not instantaneous; its speed is reflected in the estimated parameter for lagged forest clearing.

⁹ The log-linear specification has two advantages in this context. First, as previously noted, it is quite general because it is a first-order approximation to an arbitrarily-specified functional relationship between F^* and its determinants. Second, it avoids the theoretical possibility of negative deforestation by imposing a lower bound of zero on F^* .

3. Data

3.1 Timely Information on Forest Clearing

Our model requires spatially-referenced data that are observed at frequent intervals. Such information is now available for tropical Asia from FORMA (Forest Monitoring for Action), a database developed by the Center for Global Development and the World Resources Institute, in consultation with Google Earth, the University of Maryland, Resources for the Future, World Bank staff, Conservation International, the Nature Conservancy and WWF. FORMA utilizes data recorded daily by the Moderate Resolution Imaging Spectrometer (MODIS), which operates on NASA's Terra and Aqua (EOS PM) satellite platforms. Although its signal-processing algorithms are relatively complex, FORMA is based on a common-sense observation: Tropical forest clearing involves the burning of biomass and a pronounced temporary or long-term change in vegetation color, as the original forest is cleared and replaced by pastures, croplands or plantations. Accordingly, FORMA constructs indicators from MODIS-derived data on the incidence of fires and changes in vegetation color as identified by the Normalized Difference Vegetation Index (NDVI). It then calibrates to local forest clearing by fitting a statistical model that relates the MODIS-based indicator values to the best available information on actual clearing in each area.

FORMA incorporates biological, economic and social diversity by dividing the monitored territory into blocks and separately fitting the model to data for the parcels in each block. The dependent variable for each pixel is coded 1 if it has actually experienced forest clearing within the relevant time period, and 0 otherwise. The MODIS-based indicator values are the independent variables. For all tropical countries except Brazil, the best identification of recent forest clearing has been published in the Proceedings of the National Academy of Sciences by

Hansen, et al. (2008), who provide estimates for 500 m² parcels in the humid tropics. FORMA is calibrated using the map of forest cover loss hotspots (henceforth referred to as the FCLH dataset) published by Hansen, et al. for the period 2000-2005.

Using the FCLH pan-tropical dataset for 2000-2005, FORMA fits the calibration model to observations on forest clearing for 1 km² cells in each country and ecoregion. As Hammer et al. (2009) document, the model's predicted spatial probability distribution provides a very close match to the spatial incidence of FCLH forest clearing. FORMA then applies the fitted model to monthly MODIS indicator data for the period after December 2005. The output for each month is a predicted forest clearing probability for each 1 km² parcel outside of previously-deforested areas, as identified in the FCLH map. FORMA selects parcels whose probabilities exceed 50%. It calculates the total number of selected parcels within a geographic area to produce an index of forest clearing activity in that area. Even small geographic areas can include thousands of 1 km² cells, so error-averaging ensures robust index values. FORMA's outputs consistently aggregate to forest clearing indicators for subnational, national and regional entities.

The advent of FORMA permits panel estimation of spatially-disaggregated forest clearing models that incorporate short- and medium-term economic dynamics, as well as previously-studied demographic and geographic determinants of forest clearing. Such econometric analysis can provide three major benefits for conservation policymakers and project planners in tiger range countries. First, its incorporation of previously-excluded short-run economic variables permits an assessment of their relative significance as drivers of forest clearing and habitat destruction. Second, by providing a clearer view of economic incentives, the results can inform the design and implementation of incentive payment systems for REDD+ programs and similar arrangements. Third, the estimation of dynamic, spatially-referenced econometric models

provides a quantitative foundation for tracking area-specific risks of forest clearing as economic and other conditions change.

3.2 Calibrating Spatial Data to Tiger Habitat Requirements

3.2.1 Spatial Tiger Habitat Units

Our research focuses on the implications of forest clearing for tiger habitat, which is subject to critical scale requirements related to the supply of prey animals. These in turn relate to local forage characteristics, which vary widely by ecosystem. Recent advances in GPS-tagging and photo-trapping have begun to support rigorously-derived estimates of tiger densities by

Table 2: Tiger Habitat Density Estimates*

Subspecies	Countries	Sex	Tigers/100 km ²	Source
Bengal	India	Mixed	6.9	Karanth, et al. (2004)
Bengal	India	Mixed	4.1 – 16.8	Karanth, et al. (1998)
Bengal Indochinese	Bangladesh, Nepal Thailand	Female	1.3 - 8.3	Smith, et al. (2007)
Malayan	Malaysia	Mixed	1.7	Kawanishi and Sunquist (2004)
Sumatran	Indonesia	Mixed	1.1	O'Brien, et al. (2003)

* Midrange estimates

subspecies. Table 2 provides a summary of recent publications. For male and female Bengal tigers, midrange estimates include 6.8/100 km² in the tropical dry forests of Panna, central India (Karanth et al. 2004), and other local estimates for India that vary from 4.1 to 16.8/100 km² (Karanth et al. 1998). A three-country study of Bengal and Indochinese female tiger densities by Smith et al. (2007) yields estimates ranging from 1.3-8.3/100 km² for Bangladesh, Nepal and Thailand. Kawanishi and Sunquist (2004) find a density of 1.7/100 km² for Malayan tigers in Taman Negara National Park, Peninsular Malaysia. In Indonesia, O'Brien et al. (2003) find a density of 1.1/100 km² for Sumatran tigers in Bukit Barisan Selatan National Park. In light of these results, we have adopted 100 km² as the spatial grid unit for our study, on the

understanding that each 100 km² cell in natural forest area is probably sufficient for tiger survival.

Each 100 km² grid unit includes 100 1 km² reporting cells from FORMA, so we are able to characterize the clearing status of each tiger-habitat unit on a continuum from 0 to 100%. The reported occurrence of significant clearing in a 1 km² FORMA reporting cell does not necessarily mean that the cell has been completely cleared. By implication, a 100% incidence of clearing (all FORMA reporting cells) in a tiger habitat unit does not mean that all forest in the unit has been cleared. Given the critically-threatened status of tigers, however, we adopt the conservative assumption that a FORMA cell with reported clearing has been completely cleared. From this assumption, we can relate the incidence of clearing in a 100 km² tiger habitat unit to its probable implications for tiger population survival. In a study for Nepal and a contiguous area in India, Smith et al. (1998) assess the effect of habitat quality on breeding Bengal tigers. Their results suggest that breeding populations can persist in areas where poor-quality habitat is less than 65% of the total, and that tigers will not occur in areas where poor-quality habitat is more than 80% of the total. Given the scarcity of such research, the uncertainty in translating estimates of good and poor habitat quality to our clearing metric, and the high territorial density of Bengal tigers relative to other subspecies (Table 1), we adopt a conservative posture for this research. In maps that display relative tiger habitat threats, we identify habitat units with 5-50% clearing incidence as significantly affected, and units with more than 50% clearing incidence as critically affected. For metrics related to habitat threats, we grade each 100 km² tiger habitat unit by the % of FORMA reporting cells with significant clearing.¹⁰

¹⁰ In this context, we have identified two important areas for future research. The first is extension of our approach to in-depth treatment of habitat connectivity, which is critical for tiger survival. Our measure provides a first approximation for degree of habitat fragmentation, but FORMA's 1-km spatial resolution can support more detailed measurement exercises. The second, which is highly relevant for future risk modeling, is the relationship between

3.2.2 Spatial Formatting of Model Data

Some of the time series variables in our dataset are national-level and do not require spatial formatting. For relevant agricultural product prices, we use an agricultural commodity price index drawn from IMF data¹¹ and adjust to constant-dollar prices using the US GDP deflator.¹² We draw exchange rate data from OANDA's historical database¹³, and real interest rate data from the World Bank's online databank.¹⁴

The other variables in our modeling exercise require large, spatially-formatted databases for current and past forest clearing, transport-related cost factors, income per capita, land cost, rainfall, elevation, population density and protected-area status. Freely-available global databases provide direct measures for these variables, with the exception of transport-related costs. For each tiger habitat unit in the panel, available proxies for transport-related costs include travel time to the nearest major city, distance to the nearest publicly-maintained road, and distance to the coast.

For FORMA-reported data, reformatting to the 100 km² grid standard involves straightforward aggregation across 1 km² reporting cells in Stata. However, the spatially-

the incidence of clearing and the health of resident tiger populations. Recent evidence suggests that more tigers can survive in partially-degraded forest habitat (i.e., habitat where logging or partial clearing has occurred) than in forests where no clearing has occurred. By implication, survival risk is not a linear monotone function of clearing incidence. Again, FORMA's 1-km spatial resolution has the potential to provide additional insights.

¹¹ Possible candidates for the monthly price index include the following IMF price series: Food; agricultural raw materials; hardwood logs (Best Quality Malaysian Meranti, import price Japan, US\$ per cubic meter) and palm oil (Malaysia Palm Oil Futures (first contract forward) 4-5 percent FFA, US\$ per metric tonne). As we explain in Section 5, the computational requirements of simultaneous estimation of variable monthly lags for exchange rates, real interest rates and agricultural product prices limit us to one index for the latter. We have chosen the IMF's food price index as the best overall index for three reasons. First, it incorporates prices for all potential agricultural products on cleared forest land. Second, for the relevant time period it is highly correlated (.90) with the palm oil price index, which could be a key driver for forest clearing in 3 of the 10 countries (Indonesia, Malaysia and, to a lesser extent, Thailand). Third, the food price index is also significantly correlated (.60) with the hardwood log price index, which could be a determinant of forest clearing in the tiger range countries. Our source is the IMF's Primary Commodity Prices database at <http://www.imf.org/external/np/res/commmod/index.asp>

¹² Source: Bureau of Economic Analysis, Table 1.1.9. Implicit Price Deflator for Gross Domestic Product. <http://www.bea.gov/national/nipaweb/index.asp>

¹³ Source: OANDA, Historical Exchange Rates. <http://www.oanda.com/currency/historical-rates>

¹⁴ Source: World Bank Databank. <http://databank.worldbank.org/ddp/home.do?Step=12&id=4&CNO=2>.

referenced determinants of forest clearing in our model are only available in other formats, so it has been necessary to reformat them to the 100 km² standard. The nearest tractable approximation for all variables is gridding to 0.1° in latitude and longitude. This is actually a conservative approximation, since the area of a 0.1° x 0.1° grid square is 123.1 km² at the equator and 107.0 km² at 30° north latitude, the northernmost extent of the tiger habitat included in this analysis.¹⁵

Table 3 presents a summary of the spatially-referenced data sources employed for our econometric and mapping exercises. We provide more complete information in Appendix 2.

4. Sumatra Illustration: Forest Clearing in Tiger Habitat

In this section, we illustrate the spatial resolution of our database with an assessment of evolving tiger habitat threats in central Sumatra during the period January 2000 to August 2011. Our illustration also previews some elements of the threat assessment methodology that will be developed for all tropical tiger habitat areas in the next phase of the research.

Figure 2 uses multiple frames to summarize the evolving threats to the Sumatran tiger's habitat in central Sumatra since 2000. The first frame identifies 8 WWF Sumatran tiger landscapes in this area: Berbek, Bukit Tigapuluh, Kerinci Seblat, Bukit Rimbang Baling, Kualar Kampar-Kerumutan, Tesso Nilo, Bukit Barisan South¹⁶ and Rimbo Panti-Batang Gadis West. Figure 2(a) overlays the tiger landscape map with 100 km² tiger habitat cells shaded by percent of 1 km² FORMA reporting cells cleared in 2000: light gray for 60-80%, and dark gray for 80-100%.¹⁷

¹⁵ At the equator, 0.1 degrees of latitude and longitude both correspond to a flat-surface distance of 11.1 km. At 30° north latitude, the latitude and longitude distances are 11.1 and 9.6 km., respectively.

¹⁶ The digital map supplied by WWF identifies an area in the northwest corner of the figure as part of Bukit-Barisan South, a national park in Sumatra that is concentrated in the southwest part of the island.

¹⁷ Using data provided by Hansen et al (2008) and the standard definition of forested area, we identify FORMA reporting cells as forested if their vegetation continuous field (vcf) indices are greater than 25. Since the entire area

Table 3: Spatially-Referenced Data Sources for Estimation and Mapping

- 1. National and provincial boundaries:** Global administrative areas database
<http://gadm.org/>
- 2. Monthly forest clearing, December 2005 – August 2011:** FORMA (Forest Monitoring for Action), www.cgdev.org/forma
- 3. Forest cover in 2000:** Vegetation Continuous Field Index, <http://www.landcover.org/data/vcf/>
- 3. Forest clearing, 2000-2005:** Forest cover loss hotspot map
<http://globalmonitoring.sdstate.edu/projects/gfm/humidtropics/data.html>
- 5. Rainfall (monthly):** PRECipitation REConstrucion over Land (PREC/L)
<ftp://ftp.cpc.ncep.noaa.gov/precip/50yr/gauge/0.5deg/>
- 6. Elevation:** SRTM 90m Digital Elevation Database v4.1, resampled to 1 km by Andy Jarvis
<https://hc.box.com/shared/1yidaheouv>
- 7. Tiger habitat:** WWF tiger landscapes shapefile. Source: World Bank
- 8. Protected areas:** World Database on Protected Areas
<http://protectedplanet.net/about>
- 9. Income per capita:** G-Econ Database on Gridded Output
http://gecon.yale.edu/sites/default/files/Gecon40_post_final.xls
- 10. Population density:** Gridded Population of the World, version 3 (GPWv3)
<http://sedac.ciesin.columbia.edu/gpw/>
- 11. Distance to nearest road:** Source road data: Digital chart of the world
<http://www.diva-gis.org/gData>
- 12. Distance to coast**

Distance to nearest coastal point for each .1° grid cell centroid calculated using ESRI ArcMap 10.0
- 13. Travel time to nearest city>50,000 population:** Travel time to major cities: A global map of Accessibility: <http://bioval.jrc.ec.europa.eu/products/gam/index.htm>
- 14. Forested land opportunity cost:** Forest Carbon Index – Price Geography
<http://www.forestcarbonindex.org/maps.html>

was forested in the pre-industrial area, we calculate pre-2000 clearing percentages for tiger habitat units from the percent of FORMA reporting cells with vcf indices less than or equal to 25. For further information see Hansen, et al. (2006).

Figure 2(a) indicates that most tiger landscape areas had not experienced heavy clearing in 2000, although extensive clearing is visible on the eastern boundaries of Berbek and Kuala Kampar-Kerumutan and some western boundary areas of Bukit Rimbang Baling, Tesso Nilo, Bukit Tigapuluh and Kuala Kampar Kerumutan. Figure 2(b), based on evidence from Hansen, et al. (2008), shows that a striking change has occurred by 2005:¹⁸ New clearing is evident in the entire western part of Kuala Kampar-Kerumutan, with critical tiger habitat loss indicated in the landscape's northwest area. Neighboring Tesso Nilo is heavily affected, with new clearing throughout the habitat and heavy clearing in the northern and southern parts. Some new clearing also appears in the western margin of Berbek, the southern part of Bukit Tigapuluh, the east-central part of Bukit Rimbang Baling, and the western part of Bukit-Barisan South.

Further rapid deterioration is evident in Figure 2(c), which is based on monthly FORMA reports from December, 2005 to August, 2011. Tesso Nilo's condition now appears fatal for tiger survival, with heavy clearing in most of the habitat area. Major degradation also threatens much of Kuala Kampar-Kerumutan, and is spreading quickly in Bukit Tigapuluh. Some extension of clearing is also evident in the other landscapes, although it is much less pronounced.

Reference to the elevation information in Figure 1 provides one quick insight into the pattern revealed by Figure 2. With the exception of Berbek, tiger habitat is rapidly disappearing in lowland central Sumatra, which has been the main locus of palm oil plantation development on the island. The areas that display little degradation to date are mostly in western highland areas that have been beyond the reach of palm oil plantation development. In these areas, clearing has been largely in the foothill margins.

¹⁸ Forest clearing for 2000-2005 has been estimated by Hansen, et al. (2008).

Figure 2: Central Sumatra, Indonesia: Forest Clearing in Tiger Habitat

2(a): Forest Clearing Through 2000

2(b): Forest Clearing, 2000 - 2005

2(c): Forest Clearing, 2000 - 2011

While we have limited this illustration to changes over five-year periods, FORMA provides the potential for similar monitoring over periods as short as one month. In the second phase of the project, we will mobilize this information in a system that provides rapid updates on clearing in and around all the tiger landscapes in tropical Asia. In addition, we will use the econometric results reported in this paper to develop and implement a spatial forecasting model that will identify probable threats to tiger habitat during the next few years.

5. Model Estimation

5.1 Specification

From equation (6), given the available data, we estimate the following model for ten tiger-range countries: Bangladesh, Cambodia, Indonesian Sumatra, India, Lao PDR, Peninsular Malaysia, Myanmar, Nepal, Thailand and Vietnam. We have not estimated the model for Bhutan because neither Hansen, et al. (2008) nor FORMA has reported any cell where significant large-scale clearing has occurred. The panel contains monthly observations for each 100 km² grid cell with non-zero forest cover in 2000.¹⁹

¹⁹ We have interpolated the annual real interest rate from the World Bank data, assigning July to the observed value in each year.

$$(7) \log \text{Clear}_{it} = \beta_0 + \beta_1 \log(\text{Clear})_{it-1} + \beta_2 \text{Time}_t + \beta_3 \log(\text{XRate})_{t-j} + \beta_4 \text{IntRate}_{t-k} + \beta_5 \log(\text{AgPrice})_{t-l} + \beta_6 \log(\text{Rain})_{it-m} + \beta_7 \log(\text{For2000})_i + \beta_8 \log(\text{Clear05})_i + \beta_9 \log(\text{Elevation})_i + \beta_{10} \text{ProtArea}_i + \beta_{11} \log(\text{Income})_i + \beta_{12} \log(\text{PopDens})_i + \beta_{13} \log(\text{TrTime})_i + \beta_{14} \log(\text{RoadDist})_i + \beta_{15} \log(\text{CoastDist})_i + \beta_{16} \log(\text{LandCost})_i + \varepsilon_{it}$$

where prior expectations on parameter signs are:²⁰

$$\beta_1, \beta_3, \beta_5, \beta_7, \beta_8, \beta_{16}^{21} > 0$$

$$\beta_4, \beta_6, \beta_9, \beta_{10}, \beta_{13}, \beta_{14}, \beta_{15} < 0$$

Clear	=	FORMA 1 km cells cleared in habitat unit i, month t
Time	=	Months since December, 2005
XRate ²²	=	Local currency/dollar exchange rate, lagged j months
IntRate	=	Real interest rate, lagged k months
AgPrice	=	Constant-dollar agricultural product price index, lagged l months
Rain	=	Rainfall in unit i, lagged m months
For2000	=	Forested 1 km cells in unit i in 2000
Clear05	=	1 km cells in unit i cleared during 2000-05
Elevation	=	Elevation (m) of unit i
ProtArea	=	Protected status of unit i (1 if includes protected area, 0 otherwise)
Income	=	Income per capita of unit i in 2005 (\$US 2005, PPP)
PopDens	=	Population density of unit i in 2005
TrTime	=	Travel time between unit i centroid and nearest city of 50,000+
RoadDist	=	Distance from centroid of unit i to nearest publicly-maintained road
CoastDist	=	Distance from centroid of unit i to nearest coastal point
LandCost	=	Land opportunity cost in unit i.
ε_{it}	=	Random error term with temporal and spatial components.

5.2 Estimation Strategy

As large, spatially-referenced databases have become available, econometric theorists have been laying the groundwork for efficient estimation of models that incorporate spatial autocorrelation. Notable contributions to the literature on computable approaches to spatial econometric analysis have been made by Agarwal, et. al. (2002); Anselin (2001, 2002), Barrios, et al. (2010); Kapoor et al. (2007); and Kelejian et al. (1998, 2004, 2006). For this exercise, we employ two newly-developed Stata routines: *spmat* (Drukker et al. 2011), which constructs the

²⁰ Expected signs are ambiguous for the time trend, income per capita and population density.

²¹ No direct measure of land cost was available for this study. We have employed a measure of land opportunity cost developed by Resources for the Future, so the expected sign is positive (i.e., the higher the value of the land in alternate uses, the greater the relative profitability of forest clearing).

²² This variable is already in rate form, so we do not use the log transformation.

spatial weights matrix for estimation, and *spglsxt*, which operationalizes the theoretical estimator developed by Kelejian, et al. (1998, 2004, 2006) and Kapoor, et al. (2007) for generalized least squares estimation using panel data with error components that are correlated spatially and temporally.

Given the large number of proximate tiger habitat units in our panel database, adjusting for spatial autocorrelation is an important part of the estimation exercise. However, estimation of a spatial panel is complicated by the need for a spatial weights matrix whose dimensionality is the product of the number of observations (many thousands of habitat units) and time periods (69 months, from December 2005 to August 2011).²³ Using present computational algorithms, it is simply infeasible to employ such enormous spatial weights matrices.

As an alternative, we have adopted a rigorous bootstrapping approach to the estimation of model parameters. For each country, each bootstrap iteration draws a random panel of 50 habitat units. This yields a spatial weights matrix whose maximum dimensionality is 3400 x 3400 (50 units x 68 months (allowing for lagged clearing)).²⁴ Using the randomly-drawn panel, we estimate fixed- and random-effects models for the variables with time series components, and estimate the fully-specified model using random effects and spatial panel adjustments.

For each of the 10 countries, we repeat the random sampling exercise enough times to guarantee robust interpretation of the results. We generate 100+K estimates, where K is the number of righthand variables in the estimation model for each country, guaranteeing 100 degrees of freedom for standard hypothesis tests.²⁵ From the 100+K estimates, we compute

²³ We compute the weights matrix using the inverse-distance algorithm in *spmat*.

²⁴ The variable lags in (7) shorten time series in varying degrees, with consequent reduction in the dimensionality of spatial weights matrices.

²⁵ In the first round of estimation, K is determined by the number of righthand variables in estimating equation (7). In the second round, K differs by country after we drop insignificant variables and variables with perverse signs. Given the second-round differences in K-values for the 10 countries, we draw sufficient random samples to guarantee 100 degrees of freedom in each case.

means, standard errors and t-statistics for all model parameters. To ensure representative estimates for each sample, we assign habitat unit panels to two groups: those with at least one cell cleared in 2005-2011, and those with no cells cleared. Then we assign within-sample representation based on overall representation of the two groups in the country in question, and randomly sample the requisite number of units in each group. Our approach has the additional advantage of providing a robust parametric test, since more conventional single estimates on full samples are always subject to the risk of undue influence from large outlying observations.

Spatial panel estimation is inevitably cumbersome, given the spatial weights matrix requirement. Potential complications have been considerably reduced in our case by the similarity of results across estimators, as shown by the full country results in Appendix Tables A1-A10. Confirmation of this similarity has enabled us to conduct an initial, computationally-burdensome estimation exercise without incorporating spatial adjustment. This exercise focuses on choosing concurrent lag specifications for our three short-run market variables: the exchange rate, real interest rate and agricultural product price index. Prior theoretical work provides no insight about the time-structure of expectations formation in this context, so our approach is empirical. Allowing for lags as long as 24 months, we perform a three-dimensional grid search for best-fit lags in which we estimate model (7) for each combination of lags for the three market variables. Imposing the joint restriction that all three parameters have the expected signs, we choose best-fit lags using a robustness criterion based on the product of t-values for the three lags.

Once we have identified the best-fit lags, we incorporate them in a first-stage 100+K sample bootstrap exercise for each country that tests all model variables for sign consistency and significance. This exercise establishes that all variables in model (7) warrant inclusion, with the

sole exception of transport time to the nearest city with 50,000+ population. This variable is not significant for any country, no matter which estimator we employ. In the final 100+K sample estimation runs for each country, we drop a few variables whose perverse signs and high significance are clearly spurious (e.g. positive, significant results for rainfall). We note these exclusions in the following discussion of estimation results.

6. Results

Appendix Tables A1-A10 report full results for the 10 tiger range countries. Each table presents fixed- and random-effects results for the time series variables alone, along with random-effects and spatial panel results for all model variables. The four sets of results are strikingly consistent for each country, variable-by-variable, in signs, magnitudes and levels of significance. We summarize the spatial panel results in Table 4, which facilitates comparison across countries.

Our estimation model includes four dynamic elements: (1) One-month-lagged clearing, for estimation of the adjustment parameter θ (equations (2) – (7)); (2) the time trend, for estimation of the average monthly rate of change determined by unobserved exogenous factors; (3) lagged adjustment of expectations to changes in the exchange rate, the real interest rate and the agricultural product price index; (4) rainfall, which exhibits large stochastic fluctuations around long-run monthly averages in many tiger habitat units.

6.1 Adjustment Dynamics and Exogenous Trends

In our dynamic model, the short-run adjustment parameter θ relates the change rate of forest clearing to the gap between current clearing and steady-state clearing, which is determined by the model's exogenous variables. In equation (7), the estimated parameter for one-month-lagged clearing is $(1-\theta)$: The smaller the estimated parameter, the greater the value of θ and the more rapid the indicated adjustment of clearing to its steady-state value. Our results suggest

some interesting differences in country responsiveness by subspecies habitat group. The estimated adjustment to exogenous shocks is nearly immediate in the Bengal tiger habitat countries (India ($\theta=.96$), Bangladesh (.99), Nepal (not significantly different from 1.0)); slower in the Sumatran and Malayan habitat countries (Indonesian Sumatra (.83), Peninsular Malaysia (.84); and intermediate (on average) in the Indochinese habitat countries (Vietnam (.93), Lao PDR (.93), Thailand (.87), Cambodia (.82), Myanmar (.80)). At the same time, it is important to note that θ relates to *monthly* changes, so even “slower” adjustments to the new steady state are effectively complete within a year.

6.2 Dynamic Responsiveness

In our model, the full impact of a change in a time-series variable only registers after clearing has adjusted to its new steady state. Full impact parameters are the products of estimated parameters from (7) and $1/\theta$.²⁶ In this section, we assess the estimates in Table 4 using full-impact adjustments that are presented in Table 5(b).

Our results suggest significant and differentiated roles for unobserved trend determinants across countries. The trend change rate in forest clearing is negative and highly significant in Indonesian Sumatra, Cambodia, Vietnam, Bangladesh, India and Nepal. It varies considerably, with the steepest declines in the Bengal tiger countries (Bangladesh (-.31%/month), Nepal (-.31%), India (-.26%)). The negative trend is less pronounced in Indonesian Sumatra (-.21%) and lowest in Cambodia (-.16%) and Vietnam (-.14%). In contrast, trend clearing is positive and highly significant in Peninsular Malaysia (.59%), Myanmar (.27%) and Lao PDR (.16%). Thailand exhibits no significant exogenous trend.

²⁶ The multiplier $1/\theta$ is derived from the steady-state version of the basic equation for model (7): $\ln F_t = (1-\theta) \ln F_{t-1} + \beta \ln X$. When $\ln F_t = \ln F_{t-1}$ (the steady state), the solution is $[1/\theta]\beta \ln X$.

Table 4: Spatial Panel Estimates, 10 Tiger Range Countries

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area

Variable	Indonesia (Sumatra)	Malaysia (Peninsular)	Cambodia	Laos	Thailand	Vietnam	Myanmar	Bangladesh	India	Nepal
Constant	-8.4072 [15.702]**	-6.4944 [20.616]**	-23.764 [18.437]**	-10.3172 [14.63]**	-6.3081 [49.453]**	-11.0685 [21.768]**	-8.6874 [23.09]**	-9.4367 [331.439]**	-7.6029 [36.91]**	-7.5015 [340.143]**
Lag Clearing (Prev. Month)	0.1714 [24.799]**	0.1646 [34.64]**	0.1759 [22.487]**	0.0673 [7.271]**	0.1317 [7.47]**	0.0658 [4.036]**	0.1974 [9.023]**	0.0149 [8.123]**	0.0439 [4.106]**	-0.0025 [1.961]
Time Trend	-0.0017 [4.545]**	0.0049 [10.565]**	-0.0013 [4.42]**	0.0015 [3.981]**	-0.0001 [.934]	-0.0013 [9.363]**	0.0022 [5.221]**	-0.0031 [141.265]**	-0.0025 [6.998]**	-0.0031 [139.975]**
Exchange Rate	0.453 [8.995]**	1.3987 [10.081]**	2.1007 [13.251]**	0.4575 [6.009]**	0.1135 [8.27]**	0.4641 [8.337]**	2.1262 [8.477]**	0.6667 [143.632]**	0.413 [7.242]**	0.2149 [59.146]**
Real Interest Rate	-0.0193 [10.02]**	-0.0101 [7.898]**		-0.0045 [8.709]**	0.0114 [1.72]	-0.0022 [5.631]**	-0.0098 [13.077]**	-0.0405 [167.411]**	-0.0382 [6.822]**	-0.0085 [32.747]**
Ag Product Price Index	0.3434 [11.139]**	0.1776 [4.468]**	0.1581 [8.504]**	0.0718 [8.362]**	0.0275 [1.688]	0.0634 [10.747]**	0.145 [11.86]**	0.0772 [76.949]**	0.0754 [5.978]**	0.1583 [68.164]**
Rainfall	-0.0183 [3.047]**	-0.0283 [4.903]**	-0.0355 [17.126]**	-0.0044 [5.542]**	-0.0005 [.544]	-0.0031 [8.176]**		-0.003 [72.938]**		-0.0022 [10.861]**
Forest Extent 2000	0.1438 [19.634]**	0.1938 [18.421]**	0.0415 [13.313]**	0.0225 [4.336]**	0.006 [3.266]**	0 [.03]	0.0137 [4.402]**	0.0019 [7.82]**	0.0049 [7.857]**	0.0042 [21.859]**
Clearing 2000-05	0.0627 [23.342]**	0.0842 [28.427]**	0.0257 [15.189]**	0.005 [7.526]**	0.0067 [10]**	0.0085 [22.188]**	0.0058 [8.036]**	0.003 [18.672]**	0.008 [11.147]**	0.0191 [23.637]**
Elevation	-0.0841 [14.014]**	-0.1017 [11.919]**	-0.0173 [3.923]**	-0.0527 [10.584]**	0.0004 [.197]	-0.004 [6.758]**	-0.003 [1.33]	-0.0087 [17.896]**	-0.0008 [.759]	-0.005 [12.541]**
Protected Area	-0.0242 [1.437]	0.0053 [.299]	0.0104 [.896]	-0.0002 [.034]	-0.0237 [5.389]**	-0.0093 [4.332]**	-0.0077 [1.055]	0.0418 [25.486]**	-0.0099 [3.437]**	-0.0113 [19.579]**
Income Per Capita	-0.1429 [4.018]**	-0.0976 [3.763]**	0.1191 [4.354]**	0.0072 [.442]	-0.0115 [2.84]**	0.0394 [7.467]**	-0.0814 [5.376]**	0.0398 [15.754]**	-0.0291 [6.48]**	-0.0078 [4.155]**
Population Density	0.0088 [1.344]	-0.024 [3.842]**	-0.0076 [1.619]	0.0135 [3.073]**	-0.0035 [1.819]	-0.0144 [10.053]**	0.0064 [2.494]**	0.0035 [6.889]**	-0.0008 [.538]	-0.0103 [11.58]**
Distance From Road				-0.0097 [4.698]**	-0.0082 [7.801]**					
Distance From Coast			-0.0142 [2.739]**	-0.0181 [5.197]**			-0.0335 [5.276]**	-0.0103 [29.881]**		
Land Opportunity Cost			0.0202 [6.029]**	0.0084 [3.544]**	0.0033 [4.793]**				0.0011 [1.23]	

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Our results suggest that forest clearing is significantly affected by short-run market forces in all 10 tiger range countries, but with widely-varying response magnitudes. Estimated elasticities for the exchange rate vary by more than an order of magnitude, with very high values in Myanmar (2.65) and Cambodia (2.55), followed by Peninsular Malaysia (1.67) and, more distantly, Bangladesh (.68), Indonesian Sumatra (.55), Vietnam (.50), Lao PDR (.49), India (.43), Nepal (.21) and Thailand (.13).

Responsiveness to real interest rates also varies by more than an order of magnitude: Bangladesh and India have the highest estimates (-.041 and -.040, respectively), followed by Indonesian Sumatra (-.023), Myanmar (-.012), Peninsular Malaysia (-.012), Nepal (-.009), Lao PDR (-.005) and Vietnam (-.002). Thailand does not exhibit significant responsiveness to the real interest rate, and the World Bank's database does not include real interest rate information for Cambodia.

Responsiveness to agricultural product prices varies about fivefold across countries, with the greatest responsiveness in the two major palm oil producers -- Indonesian Sumatra (.41), and Peninsular Malaysia (.21) -- followed in close succession by Cambodia (.19), Myanmar (.18), Nepal (.16), and, in a lower cluster, India (.08), Bangladesh (.08), Lao PDR (.08), and Vietnam (.07). Again, Thailand exhibits no responsiveness.

Tables A1-A10 present our best-fit lag estimates by country for exchange rates, real interest rates and agricultural product prices. The summary in Table 6 suggests similar adjustment timing for the exchange rate, with lags clustered between 17 and 24 months. In contrast, lags for the real interest rate vary from 1-2 months at one extreme to 20-21 months at the other, with relatively few intermediate values. A different pattern characterizes lags for agricultural input prices, which are in a rough continuum from 1 to 23 months. Part of the difference in price responsiveness may well be explained by cross-country variations in the relative importance of commodities with different production economics (e.g., timber, palm oil).

Table 5: Country Response Sensitivity

Country		Time Trend	Exchange Rate	Real Interest Rate	Ag Product Price Index	Rainfall
(5a)	Median	Index (Absolute Values: Max 100)				
Cambodia	71	27	96		46	100
Malaysia (Peninsular)	63	100	63	29	51	79
Indonesia (Sumatra)	51	35	21	57	100	51
Myanmar	45	47	100	30	44	
India	32	45	16	97	19	
Bangladesh	26	54	26	100	19	7
Nepal	21	53	8	21	38	5
Lao PDR	19	27	19	12	19	11
Vietnam	16	24	19	6	16	8
Thailand	0	0	5	0	0	1
(5b)	Multiplier (1/θ)	Steady-State Parameter Estimates				
Cambodia	1.21	-0.0016	2.55		0.192	-0.0431
Malaysia (Peninsular)	1.20	0.0059	1.67	-0.0121	0.213	-0.0339
Indonesia (Sumatra)	1.21	-0.0021	0.55	-0.0233	0.414	-0.0221
Myanmar	1.25	0.0027	2.65	-0.0122	0.181	
India	1.05	-0.0026	0.43	-0.0400	0.079	
Bangladesh	1.02	-0.0031	0.68	-0.0411	0.078	-0.0030
Nepal	1.00	-0.0031	0.21	-0.0085	0.158	-0.0022
Lao PDR	1.07	0.0016	0.49	-0.0048	0.077	-0.0047
Vietnam	1.07	-0.0014	0.50	-0.0024	0.068	-0.0033
Thailand	1.15	0.0000	0.13	0.0000	0.000	-0.0006
(5c)	Lagged Clearing (1-θ)	Parameter Estimates (Table 4)				
Cambodia	0.176	-0.0013	2.10		0.158	-0.0355
Malaysia (Peninsular)	0.165	0.0049	1.40	-0.0101	0.178	-0.0283
Indonesia (Sumatra)	0.171	-0.0017	0.45	-0.0193	0.343	-0.0183
Myanmar	0.197	0.0022	2.13	-0.0098	0.145	
India	0.044	-0.0025	0.41	-0.0382	0.075	
Bangladesh	0.015	-0.0031	0.67	-0.0405	0.077	-0.0030
Nepal	0.000	-0.0031	0.21	-0.0085	0.158	-0.0022
Lao PDR	0.067	0.0015	0.46	-0.0045	0.072	-0.0044
Vietnam	0.066	-0.0013	0.46	-0.0022	0.063	-0.0031
Thailand	0.132		0.11			-0.0005

Table 6: Best-Fit Country Response Lags (Months)

Country	Exchange Rate	Real Interest Rate	Ag. Product Price
Indonesian Sumatra	19	13	2
Peninsular Malaysia	19	20	15
Myanmar	23	1	12
Laos	19	21	1
Vietnam	17	11	2
Thailand	24	10	23
Cambodia	20		21
India	17	2	9
Bangladesh	22	1	16
Nepal	20	21	21

Rainfall is also a source of significant stochastic shocks, so we include it in our treatment of dynamic response. We find a common, significant, two-month lag for rainfall's negative impact on forest clearing in 7 of the tiger range countries. Perverse results are implausible in this context, so we have dropped rainfall from final estimation in the two countries – Myanmar and India -- where its estimated parameter is positive and significant. Rainfall has the appropriate sign and high levels of significance for all other tiger range countries except Thailand, with the greatest responsiveness in Cambodia (-.043), Peninsular Malaysia (-.033) and Indonesian Sumatra (-.022).

Although responsiveness to individual variables is certainly of interest, the overall pattern of results provides an opportunity to learn more about the general responsiveness of the tiger range countries to dynamic factors. In Table 5, we present three variants of the results for the time trend, exchange rate, real interest rate, agricultural product prices, and rainfall. Table (5c) reproduces the spatial panel estimation results from Table 4, along with the estimated parameters $(1-\theta)$ for lagged clearing. In (5b), we calculate the dynamic response multipliers $(1/\theta)$ and multiply them by the estimates in (5c) to produce full impact parameter estimates. These are the estimates that we have used for the previous discussion. Table (5a) further transforms the estimates to a format appropriate

for overall assessment: We convert all estimates to absolute values and re-express them as indices with maximum values of 100. Then we calculate median index values, presented in the first column of (5a), and tabulate them in descending order.

The results indicate clear differences in overall responsiveness for countries that harbor different tiger subspecies. For Sumatran and Malayan tiger habitat countries, the dynamic responsiveness index is high (63 and 51, respectively). Responsiveness is substantially lower in the Bengal tiger habitat countries, which are clustered together (India 32, Bangladesh 26, Nepal 21). In contrast, habitat countries for the Indochinese tiger occupy the entire range of sensitivity, from the highest (Cambodia 71), through the mid-range (Myanmar 45), to very low values (Lao PDR 19, Vietnam 19, Thailand 0).

These results are unfortunate, because dynamic sensitivity is an important form of vulnerability in this context. As we have noted, Sumatran and Malayan tigers have been reduced to very small populations in highly-confined areas. In addition, our results indicate that these areas are highly susceptible to dynamic market shocks and changes in rainfall. In contrast, the Bengal tiger is spread across three countries that exhibit much lower dynamic sensitivity. For the Indochinese tiger, our results suggest careful attention to conditions in specific countries: Cambodia has very high sensitivity, for example, while Thailand apparently has none. By extension, fully-accounted vulnerability for Indochinese tigers is much higher (*ceteris paribus*) in Cambodia and Myanmar than in Lao PDR, Vietnam and Thailand.

Unfortunately, our results for forest protection reinforce this pattern of vulnerability. We provide a first-order test of national conservation policies with a dummy variable for habitat units that include formally-protected areas. Controlling for the other forest clearing determinants²⁷, our

²⁷ As Nelson and Chomitz (2009) note, statistical control for other variables is critical in this context because the location of protected areas may be systematically related to other determinants of forest clearing. For example, protected areas

results suggest that formal protection has significantly reduced forest clearing in 4 of the 10 countries: Thailand, Nepal, India and Vietnam. We obtain a perverse result for Bangladesh, where clearing is significantly higher in protected areas, *ceteris paribus*. We find no significant effect for protection in the other 5 countries. In particular, we find no evidence that formal protection slows forest clearing in the highest-sensitivity countries (Indonesian Sumatra, Peninsular Malaysia, Cambodia, Myanmar). This contrasts with strong evidence that protection has a significant conservation effect in several low-sensitivity countries (Thailand, Vietnam, India and Nepal).

In summary, our estimation exercise reveals a pattern of appropriately-signed and highly-significant responsiveness to unobserved trend determinants, short-run market variables and exogenous rainfall shocks in all 10 tiger range countries. At the same time, they differ greatly in estimated response magnitudes and adjustment timing for real interest rates and agricultural product prices. Overall, our results add an additional element of vulnerability that is particularly worrisome for Sumatran and Malayan tigers (as well as Indochinese tigers in Cambodia and Myanmar). Our results for protection compound the concern.

Empirical work of this type was not feasible before the advent of FORMA, so we have no cross-check from other empirical studies. Although further research will undoubtedly deepen our insights, we believe that our results are sufficiently robust to highlight a critical message for the conservation policy community: Changes in world agricultural product markets and national financial policies have significant effects on tropical forest clearing and species vulnerability (particularly for Sumatran and Malayan tigers), with variable time lags and degrees of responsiveness across countries. Measuring these effects and pinpointing areas at risk can provide

may be disproportionately located in high-elevation forests that are distant from transport infrastructure, so exclusion of these variables from an evaluation of protected-area status will ascribe too much conservation effect to protection.

valuable guidance for policymakers, conservation managers, and donor institutions. In addition, this information may well be useful for baseline-setting in REDD+ programs.

6.3 Environmental and Structural Factors

Our scaling variable, natural forest extent in 2000, has the expected sign and high significance for all countries except Lao PDR, where it is not significant. The result is even stronger for clearing in 2000-05, which has the expected positive sign and very high significance in all 10 countries. As in the case of rainfall, the countries where prior clearing has the greatest effect are Peninsular Malaysia (elasticity .08), Indonesian Sumatra (.06) and Cambodia (.03). Although this variable may reflect some unobserved determinants of local forest clearing, we believe that the most plausible interpretation relates to scale economies: Once clearing infrastructure is in place (e.g. relevant supplies, services, equipment, roads), it is less costly to clear at the local forest margin than to begin clearing at new sites.

For elevation, we again find particularly high responsiveness in Peninsular Malaysia (-.10) and Indonesian Sumatra (-.08). These results probably reflect the decline in oil palm productivity with altitude, since this sector has been a major driver of forest clearing in both countries.

Our results for physical determinants of transport cost are highly varied. Forest clearing in half of the countries exhibits significant sensitivity to distance from the nearest publicly-maintained road or the nearest coastal point. On the other hand, half the countries exhibit no sensitivity or perverse positive results, and none of the countries exhibit sensitivity to our other distance-related variable, transport time to the nearest major city. For our final estimation runs, we have retained variables with the appropriate sign and high significance.

We find the same scattered responsiveness for land opportunity cost, which is positive and significant in only 3 of the 10 countries. However, we recognize that all factors in our model affect

profitability calculations, and therefore opportunity costs, so this variable may be redundant to some degree.

The expected sign of income per capita is ambiguous in our theoretical model, so it is not surprising that our results for this variable are mixed. The negative factors (low-skill wages; conservation policy) appear to dominate in Indonesian Sumatra (elasticity $-.14$) and Peninsular Malaysia ($-.10$), as well as Myanmar ($-.08$), India ($-.03$) and Thailand ($-.01$). In contrast, the positive factors (local demand elements) appear to dominate in Cambodia ($.11$), Bangladesh ($.04$) and Vietnam ($.03$). We find no effect in Lao PDR.

We obtain similarly-varied results for population density, which is significant in 6 of the 10 countries. The measured impact is negative in Peninsular Malaysia (elasticity $-.02$), Vietnam ($-.01$) and Nepal ($-.01$), suggesting the dominance of prior clearing. On the other hand, positive results for Lao PDR [$.01$], Myanmar [$.006$] and Bangladesh [$.004$] suggest a dominant role for population pressure in these countries.

7. Summary and Conclusions

In this paper, we have described and illustrated the development of two critical inputs to the estimation of habitat threat for Bengal, Indochinese, Malayan and Sumatran tigers. The first is a spatially-formatted 10-country panel database that integrates high-resolution monthly forest clearing information from FORMA (Forest Monitoring for Action) with data for a large number of variables that are potential determinants of forest clearing in tropical Asia. The database includes Bangladesh, Cambodia, India, Indonesia, Lao PDR, Malaysia, Myanmar, Nepal, Thailand and Vietnam. The second input is an econometric model of forest clearing that uses spatial panel estimation techniques to assess the significance and magnitude of forest clearing's responses to its determinants in each country. Both inputs will contribute to a system for estimating the severity of threats to 74 surviving

tiger habitat areas identified by WWF and other conservation organizations. The system will feature color-coded threat mapping, as well as quantified threat estimates that can assist in identifying critical habitat areas for support by the Global Tiger Initiative. It will also draw on the econometric results to provide threat forecasts for the next few years. We will describe and illustrate the fully-developed system in a forthcoming paper.

In Sections 3 and 4, we describe the 10-country panel database and illustrate its potential with an assessment of evolving threats to tiger habitat in central Sumatra, Indonesia. Our empirical approach uses a spatial grid unit of 100 km^2 , which approximates the critical minimum habitat size for tiger survival. For each 100 km^2 unit, we grade habitat quality by the percent of 1 km^2 FORMA reporting cells where significant forest clearing has occurred. In the Sumatra illustration, we track the progressive destruction of habitat in 8 tiger habitat areas from January 2000 to August 2011.

In Sections 2, 5 and 6, we develop and test an econometric model of forest clearing that can be used for policy analysis and threat forecasting. The model links forest clearing to profitability calculations that are affected by market expectations, environmental conditions, and evolving patterns of settlement, economic activity, infrastructure provision and regulatory activity. In each 100 km^2 habitat unit, the scale of clearing reflects the extent of uncleared forest; scale economies from previous clearing (2000-2005); elevation; income; population density; transport-related costs; the cost of the forested land; and conservation policy. Clearing may also exhibit an exogenous trend that reflects unobserved economic, environmental and regulatory forces. In each month, the evolution of clearing in response to all these factors is perturbed by two types of stochastic shocks in the model: Variations in local rainfall, and market-induced revisions of expectations about future levels of the exchange rate, the real interest rate, and the prices of agricultural commodities that could be produced if the forested land were cleared. Full adjustment to these changing factors is not

instantaneous, and the model permits estimation of adjustment speed by incorporating lagged forest clearing.

We have estimated the model with newly-developed spatial panel estimation methods that allow for both temporal and spatial autocorrelation. Our results indicate significant roles for all model variables, with considerable variation in estimated response timing and impact elasticities across countries. We believe that our results for the exchange rate, real interest rate and agricultural product prices are of particular interest, because empirical impact assessment for these theoretically-important variables was simply not feasible before the advent of FORMA. Overall, we find clear differences in responsiveness to dynamic factors (unobserved determinants of trend clearing, short-run market variables, rainfall). Unfortunately, this sensitivity is quite high for the habitat countries of two highly-endangered subspecies, Sumatran and Malaysian tigers. Their vulnerability is further highlighted by our results for formal protection, which has no measured effect for Indonesian Sumatra or Peninsular Malaysia, but significant effects for the low-sensitivity habitat countries of Bengal tigers. Although the latter are seriously threatened, they are more numerous and more widely-dispersed than the Sumatran and Malayan subspecies.

This approach to habitat vulnerability research is new, and more will undoubtedly be learned from future work. However, the general pattern of our results seems sufficiently robust for us to highlight a critical message for the conservation policy community: *Changes in world agricultural product markets and national financial policies have significant, measurable effects on tropical forest clearing, with variable time lags and degrees of responsiveness across countries. Measuring these effects and pinpointing areas at risk can provide valuable guidance for policymakers, conservation managers, and donor institutions. In addition, this information may well be useful for baseline-setting in REDD+ programs.* The estimation of response lags for these critical market

variables will also provide a key input to forecasting tiger habitat threats, which will be the focus of the next paper.

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Table A1: Indonesia (Sumatra)

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area
Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-7.759 [18.643]**	-9.2903 [20.529]**	-7.4459 [15.292]**	-8.4072 [15.702]**
Lag Clearing (Prev. Month)	0.3645 [45.711]**	0.1992 [30.14]**	0.3177 [40.445]**	0.1714 [24.799]**
Time Trend	-0.0014 [4.804]**	-0.0016 [4.37]**	-0.0015 [4.872]**	-0.0017 [4.545]**
Exchange Rate [19]	0.4006 [8.846]**	0.4519 [9.205]**	0.4307 [9.257]**	0.453 [8.995]**
Real Interest Rate [13]	-0.0159 [9.484]**	-0.019 [9.702]**	-0.0175 [10.052]**	-0.0193 [10.02]**
Ag Product Price Index [2]	0.2823 [10.625]**	0.3293 [10.741]**	0.3091 [11.235]**	0.3434 [11.139]**
Rainfall [2]	-0.021 [3.11]**	-0.0268 [4.49]**	-0.0119 [1.818]	-0.0183 [3.047]**
Forest Extent 2000			0.1175 [20.135]**	0.1438 [19.634]**
Clearing 2000-05			0.0517 [23.575]**	0.0627 [23.342]**
Elevation			-0.0685 [14.044]**	-0.0841 [14.014]**
Protected Area			-0.0213 [1.525]	-0.0242 [1.437]
Income Per Capita			-0.1204 [4.119]**	-0.1429 [4.018]**
Population Density			0.0079 [1.48]	0.0088 [1.344]

 $H_0: \beta=0$: ** Rejection at 99% significance; * 95% significance

Table A2: Malaysia (Peninsular)

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area
Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-6.1657 [35.929]**	-7.3578 [37.984]**	-5.9825 [21.625]**	-6.4944 [20.616]**
Lag Clearing (Prev. Month)	0.297 [54.914]**	0.1523 [36.292]**	0.255 [49.544]**	0.1646 [34.64]**
Time Trend	0.0045 [11.374]**	0.0054 [11.571]**	0.0048 [11.472]**	0.0049 [10.565]**
Exchange Rate [19]	1.2789 [10.366]**	1.4731 [10.489]**	1.3241 [10.269]**	1.3987 [10.081]**
Real Interest Rate [20]	-0.01 [9.034]**	-0.0112 [8.598]**	-0.0103 [8.869]**	-0.0101 [7.898]**
Ag Product Price Index [15]	0.1601 [4.543]**	0.1806 [4.537]**	0.1638 [4.451]**	0.1776 [4.468]**
Rainfall [2]	-0.0272 [4.652]**	-0.0293 [5.064]**	-0.0303 [5.025]**	-0.0283 [4.903]**
Forest Extent 2000			0.1738 [18.034]**	0.1938 [18.421]**
Clearing 2000-05			0.074 [30.449]**	0.0842 [28.427]**
Elevation			-0.097 [13.235]**	-0.1017 [11.919]**
Protected Area			0.0063 [.416]	0.0053 [.299]
Income Per Capita			-0.0731 [3.169]**	-0.0976 [3.763]**
Population Density			-0.0223 [4.052]**	-0.024 [3.842]**

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Table A3: Cambodia

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend and Protected Area

Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-20.9021 [17.551]**	-24.74 [18.751]**	-21.0823 [17.128]**	-23.764 [18.437]**
Lag Clearing (Prev. Month)	0.2696 [31.914]**	0.1379 [19.661]**	0.2413 [30.165]**	0.1759 [22.487]**
Time Trend	-0.0014 [5.226]**	-0.0014 [4.807]**	-0.0011 [3.757]**	-0.0013 [4.42]**
Exchange Rate [20]	1.9433 [13.423]**	2.3017 [14.283]**	1.8378 [12.139]**	2.1007 [13.251]**
Ag Product Price Index [21]	0.1632 [9.736]**	0.1618 [8.429]**	0.1408 [7.945]**	0.1581 [8.504]**
Rainfall [2]	-0.0302 [16.61]**	-0.036 [17.113]**	-0.0354 [17.196]**	-0.0355 [17.126]**
Forest Extent 2000			0.0363 [14.302]**	0.0415 [13.313]**
Clearing 2000-05			0.0239 [15.727]**	0.0257 [15.189]**
Elevation			-0.0148 [3.874]**	-0.0173 [3.923]**
Protected Area			0.0157 [1.605]	0.0104 [.896]
Income Per Capita			0.1086 [4.382]**	0.1191 [4.354]**
Population Density			-0.005 [1.211]	-0.0076 [1.619]
Distance From Coast			-0.0115 [2.443]**	-0.0142 [2.739]**
Land Opportunity Cost			0.0181 [6.048]**	0.0202 [6.029]**

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Table A4: Lao PDR

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area

Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-10.1075 [15.745]**	-10.7479 [14.732]**	-9.8509 [14.906]**	-10.3172 [14.63]**
Lag Clearing (Prev. Month)	0.1114 [9.182]**	0.0478 [4.81]**	0.0946 [8.213]**	0.0673 [7.271]**
Time Trend	0.0014 [4.297]**	0.0015 [3.957]**	0.0013 [3.796]**	0.0015 [3.981]**
Exchange Rate [19]	0.4399 [6.371]**	0.4632 [5.951]**	0.4245 [5.967]**	0.4575 [6.009]**
Real Interest Rate [21]	-0.0041 [8.333]**	-0.0047 [8.664]**	-0.0043 [8.636]**	-0.0045 [8.709]**
Ag Product Price Index [1]	0.0737 [8.747]**	0.0775 [8.673]**	0.0715 [8.417]**	0.0718 [8.362]**
Rainfall [2]	-0.0041 [5.615]**	-0.0038 [4.876]**	-0.0043 [5.757]**	-0.0044 [5.542]**
Forest Extent 2000			0.0201 [4.232]**	0.0225 [4.336]**
Clearing 2000-05			0.0047 [8.148]**	0.005 [7.526]**
Elevation			-0.0486 [11.203]**	-0.0527 [10.584]**
Protected Area			-0.0027 [.633]	-0.0002 [.034]
Income Per Capita			0.0071 [.529]	0.0072 [.442]
Population Density			0.0141 [3.454]**	0.0135 [3.073]**
Distance From Road			-0.0074 [5.051]**	-0.0097 [4.698]**
Distance From Coast			-0.0169 [6.053]**	-0.0181 [5.197]**
Land Opportunity Cost			0.008 [3.872]**	0.0084 [3.544]**

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Table A5: Thailand

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area

Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-6.166 [50.426]**	-6.7677 [55.556]**	-6.1454 [47.744]**	-6.3081 [49.453]**
Lag Clearing (Prev. Month)	0.1664 [9.057]**	0.0805 [4.605]**	0.1559 [8.57]**	0.1317 [7.47]**
Time Trend	0.0000 [.37]	-0.0002 [1.943]	0.0000 [.436]	-0.0001 [.934]
Exchange Rate [24]	0.1155 [8.671]**	0.105 [7.667]**	0.1145 [8.669]**	0.1135 [8.27]**
Real Interest Rate [10]	0.0051 [.885]	0.0211 [2.653]**	0.0084 [1.341]	0.0114 [1.72]
Ag Product Price Index [23]	0.0299 [2.007]*	0.015 [.842]	0.0271 [1.662]	0.0275 [1.688]
Rainfall [2]	-0.0013 [1.623]	0.0002 [.248]	-0.0009 [1.06]	-0.0005 [.544]
Forest Extent 2000			0.004 [3.148]**	0.006 [3.266]**
Clearing 2000-05			0.0063 [11.453]**	0.0067 [10]**
Elevation			0.0032 [2.049]*	0.0004 [.197]
Protected Area			-0.0202 [5.469]**	-0.0237 [5.389]**
Income Per Capita			-0.013 [3.321]**	-0.0115 [2.84]**
Population Density			-0.0018 [1.028]	-0.0035 [1.819]
Distance From Road			-0.0077 [8.315]**	-0.0082 [7.801]**
Land Opportunity Cost			0.0042 [7.235]**	0.0033 [4.793]**

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Table A6: Vietnam

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area
Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-10.8791 [21.806]**	-10.9717 [21.192]**	-10.9232 [21.587]**	-11.0685 [21.768]**
Lag Clearing (Prev. Month)	0.0835 [5.135]**	0.0445 [3.009]**	0.0741 [4.626]**	0.0658 [4.036]**
Time Trend	-0.0014 [9.61]**	-0.0013 [8.911]**	-0.0013 [9.259]**	-0.0013 [9.363]**
Exchange Rate [17]	0.4755 [8.515]**	0.4575 [7.885]**	0.4561 [8.179]**	0.4641 [8.337]**
Real Interest Rate [11]	-0.0022 [5.828]**	-0.0021 [5.232]**	-0.0021 [5.473]**	-0.0022 [5.631]**
Ag Product Price Index [2]	0.0651 [11.012]**	0.0655 [10.789]**	0.0644 [10.839]**	0.0634 [10.747]**
Rainfall [2]	-0.0023 [6.513]**	-0.0034 [8.889]**	-0.0031 [8.352]**	-0.0031 [8.176]**
Forest Extent 2000			-0.0001 [.164]	0.0000 [.03]
Clearing 2000-05			0.0085 [23.005]**	0.0085 [22.188]**
Elevation			-0.0038 [6.898]**	-0.004 [6.758]**
Protected Area			-0.0087 [4.524]**	-0.0093 [4.332]**
Income Per Capita			0.0375 [7.209]**	0.0394 [7.467]**
Population Density			-0.0138 [10.654]**	-0.0144 [10.053]**

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Table A7: Myanmar

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area
Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-8.9051 [22.859]**	-9.8642 [23.358]**	-8.3845 [22.64]**	-8.6874 [23.09]**
Lag Clearing (Prev. Month)	0.2506 [10.877]**	0.1557 [7.701]**	0.2291 [10.464]**	0.1974 [9.023]**
Time Trend	0.0019 [4.664]**	0.0024 [5.436]**	0.002 [4.911]**	0.0022 [5.221]**
Exchange Rate [23]	2.0266 [8.318]**	2.1871 [8.226]**	2.0684 [8.281]**	2.1262 [8.477]**
Real Interest Rate [1]	-0.0092 [13.104]**	-0.0102 [13.168]**	-0.0094 [13.142]**	-0.0098 [13.077]**
Ag Product Price Index [12]	0.1375 [12.077]**	0.1496 [12.027]**	0.1401 [12.052]**	0.145 [11.86]**
Forest Extent 2000			0.0123 [4.279]**	0.0137 [4.402]**
Clearing 2000-05			0.0055 [7.948]**	0.0058 [8.036]**
Elevation			-0.0035 [1.727]	-0.003 [1.33]
Protected Area			-0.0071 [1.033]	-0.0077 [1.055]
Income Per Capita			-0.0775 [5.88]**	-0.0814 [5.376]**
Population Density			0.0047 [2.083]*	0.0064 [2.494]**
Distance From Coast			-0.0316 [5.631]**	-0.0335 [5.276]**

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Table A8: Bangladesh

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area

Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-9.261 [4137.394]**	-9.4066 [3845.952]**	-9.6333 [498.058]**	-9.4367 [331.439]**
Lag Clearing (Prev. Month)	-0.0008 [273.815]**	-0.0362 [322.339]**	-0.0163 [76.584]**	0.0149 [8.123]**
Time Trend	-0.003 [193.862]**	-0.0031 [189.137]**	-0.0031 [165.091]**	-0.0031 [141.265]**
Exchange Rate [22]	0.6584 [1942.437]**	0.6371 [1243.987]**	0.6648 [818.425]**	0.6667 [143.632]**
Real Interest Rate [1]	-0.0413 [511.093]**	-0.0424 [429.968]**	-0.0424 [364.824]**	-0.0405 [167.411]**
Ag Product Price Index [16]	0.0743 [96.908]**	0.0766 [96.57]**	0.0789 [87.61]**	0.0772 [76.949]**
Rainfall [2]	-0.0034 [107.229]**	-0.0032 [105.252]**	-0.0031 [98.292]**	-0.003 [72.938]**
Forest Extent 2000			0.002 [8.489]**	0.0019 [7.82]**
Clearing 2000-05			0.0029 [17.999]**	0.003 [18.672]**
Elevation			-0.0082 [16.556]**	-0.0087 [17.896]**
Protected Area			0.0395 [26.171]**	0.0418 [25.486]**
Income Per Capita			0.0403 [16.128]**	0.0398 [15.754]**
Population Density			0.0037 [7.065]**	0.0035 [6.889]**
Distance From Coast			-0.0109 [31.765]**	-0.0103 [29.881]**

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Table A9: India

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area
Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-7.7663 [40.242]**	-8.2313 [42.455]**	-7.5962 [37.411]**	-7.6029 [36.91]**
Lag Clearing (Prev. Month)	0.0539 [5.812]**	-0.0051 [.536]	0.0434 [4.767]**	0.0439 [4.106]**
Time Trend	-0.0026 [7.033]**	-0.0027 [7.04]**	-0.0026 [7.015]**	-0.0025 [6.998]**
Exchange Rate [17]	0.4108 [7.222]**	0.4295 [7.48]**	0.4132 [7.266]**	0.413 [7.242]**
Real Interest Rate [2]	-0.0386 [6.821]**	-0.04 [6.983]**	-0.0387 [6.841]**	-0.0382 [6.822]**
Ag Product Price Index [9]	0.0744 [5.956]**	0.0772 [6.1]**	0.0748 [5.974]**	0.0754 [5.978]**
Forest Extent 2000			0.0049 [8.141]**	0.0049 [7.857]**
Clearing 2000-05			0.0082 [11.423]**	0.008 [11.147]**
Elevation			-0.0008 [.795]	-0.0008 [.759]
Protected Area			-0.0108 [3.856]**	-0.0099 [3.437]**
Income Per Capita			-0.0296 [6.516]**	-0.0291 [6.48]**
Population Density			-0.0011 [.717]	-0.0008 [.538]
Land Opportunity Cost			0.0013 [1.414]	0.0011 [1.23]

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Table A10: Nepal

Dependent Variable: Log Monthly Forest Clearing

All variables in logs except Time Trend, Real Interest Rate and Protected Area
Months lagged: [M]

Variable	Random	Fixed	Random	Spatial
Constant	-7.7474 [535.403]**	-7.9631 [549.817]**	-7.5985 [394.872]**	-7.5015 [340.143]**
Lag Clearing (Prev. Month)	-0.0052 [49.403]**	-0.0285 [259.247]**	-0.0135 [30.782]**	-0.0025 [1.961]
Time Trend	-0.0031 [183.993]**	-0.0032 [164.212]**	-0.0031 [169.132]**	-0.0031 [139.975]**
Exchange Rate [20]	0.2182 [62.342]**	0.232 [66.292]**	0.2219 [63.292]**	0.2149 [59.146]**
Real Interest Rate [21]	-0.0085 [32.45]**	-0.0088 [33.199]**	-0.0087 [33.591]**	-0.0085 [32.747]**
Ag Product Price Index [21]	0.1577 [76.664]**	0.1674 [69.961]**	0.1621 [72.96]**	0.1583 [68.164]**
Rainfall [2]	-0.0024 [12.375]**	-0.0021 [10.42]**	-0.0021 [10.856]**	-0.0022 [10.861]**
Forest Extent 2000			0.0042 [22.522]**	0.0042 [21.859]**
Clearing 2000-05			0.0194 [23.234]**	0.0191 [23.637]**
Elevation			-0.0048 [12.09]**	-0.005 [12.541]**
Protected Area			-0.0117 [21.52]**	-0.0113 [19.579]**
Income Per Capita			-0.0086 [4.775]**	-0.0078 [4.155]**
Population Density			-0.0103 [11.772]**	-0.0103 [11.58]**

H₀: β=0: ** Rejection at 99% significance; * 95% significance

Appendix 2: Spatially-Referenced Data Used for Estimation and Mapping

1. National and provincial boundaries: Global administrative areas database

<http://gadm.org/>

2. Monthly forest clearing, December 2005 – August 2011: FORMA (Forest Monitoring for Action), www.cgdev.org/forma

Resolution: 1 km

Projection: Lat/long

Aggregated to 0.1° lat/long projection using Stata

Citation: Hammer, Daniel, Robin Kraft and David Wheeler. 2009. FORMA: Forest Monitoring for Action—Rapid Identification of Pan-tropical Deforestation Using Moderate-Resolution Remotely Sensed Data. Center for Global Development Working Paper No. 192, November.

3. Forest cover in 2000: Vegetation Continuous Field

<http://www.landcover.org/data/vcf/>

Estimates vegetation cover globally using MODIS data. Used in FORMA as a forest mask (VCF pixel value > 25%).

Data format: HDF4

Pixel size: 926.6254331 m

Projection: Sinusoidal

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation: Hansen, M., R. DeFries, J.R. Townshend, M. Carroll, C. Dimiceli, and R. Sohlberg. 2006. Vegetation Continuous Fields MOD44B, 2001 Percent Tree Cover, Collection 4, University of Maryland, College Park, Maryland, 2001.

3. Forest clearing, 2000-2005: Forest cover loss hotspot map

<http://globalmonitoring.sdstate.edu/projects/gfm/humidtropics/data.html>

Data format: GeoTiff. 8-bit unsigned integer data.

Pixel size: 463.3127m.

Projection: Sinusoidal

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation: Hansen, M.C., Stehman, S.V., Potapov, P.V., Loveland, T.R., Townshend, J.R.G., DeFries, R.S., Pittman, K.W., Stolle, F., Steininger, M.K., Carroll, M., Dimiceli, C. 2008. Humid tropical forest clearing from 2000 to 2005 quantified using multi-temporal and multi-resolution remotely sensed data. PNAS, 105(27), 9439-9444.

5. Rainfall (monthly): PRECipitation REConstruction over Land (PREC/L)

<ftp://ftp.cpc.ncep.noaa.gov/precip/50yr/gauge/0.5deg/>

Data format: binary time series

Resolution: 0.5 degrees

Projection: Lat/long

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation: Chen, M., P. Xie, J. E. Janowiak, and P. A. Arkin. 2002. Global Land Precipitation: A 50-yr Monthly Analysis Based on Gauge Observations, *J. Hydrometeor.*, 3, 249-266.

6. Elevation: SRTM 90m Digital Elevation Database v4.1, resampled to 1 km by Andy Jarvis

<https://hc.box.com/shared/1yidaheouv> (Password ThanksCSI!)

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation: Jarvis, A., H.I. Reuter, A. Nelson, E. Guevara. 2008. Hole-filled SRTM for the globe Version 4, available from the CGIAR-CSI SRTM 90m Database (<http://srtm.csi.cgiar.org>).

7. Tiger habitat: WWF tiger landscapes shapefile. Source: World Bank

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation: Wildlife Conservation Society, World Wildlife Fund, Smithsonian Institution, Save the Tiger Fund (WCS, WWF, Smithsonian, STF). 2006. Setting Priorities for Conservation and Recovery of Wild Tigers 2005-2010. Funded by Save the Tiger Fund, the Critical Ecosystem Partnership Fund, the United Nations Foundation, and the Zoological Society of London. July 2006.

8. Protected areas: World Database on Protected Areas

<http://protectedplanet.net/about>

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation: WDPA (Content Source); Juan Pablo Arce (Topic Editor) "World Database on Protected Areas". In: Encyclopedia of Earth. Eds. Cutler J. Cleveland (Washington, D.C.: Environmental Information Coalition, National Council for Science and the Environment)\ http://www.eoearth.org/article/World_Database_on_Protected_Areas

9. Income per capita: G-Econ Database on Gridded Output

http://gecon.yale.edu/sites/default/files/Gecon40_post_final.xls

Resolution: 1 degree

Projection: Lat/long

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation: Nordhaus, William, Qazi Azam, David Corderi, Kyle Hood, Nadejda Makarova Victor, Mukhtar Mohammed, Alexandra Miltner, and Jyldyz Weiss. 2006. The G-Econ Database on Gridded Output: Methods and Data. Yale University.

http://gecon.yale.edu/sites/default/files/gecon_data_20051206.pdf

10. Population density: Gridded Population of the World, version 3 (GPWv3)

<http://sedac.ciesin.columbia.edu/gpw/>

Resolution: 1/4 degree

Projection: Lat/long

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation: Center for International Earth Science Information Network (CIESIN), Columbia University; United Nations Food and Agriculture Programme (FAO); and Centro Internacional de Agricultura Tropical (CIAT). 2005. Gridded Population of the World: Future Estimates (GPWFE). Palisades, NY: Socioeconomic Data and Applications Center (SEDAC), Columbia University.

11. Distance to nearest road: Source road data: Digital chart of the world

<http://www.diva-gis.org/gData>

Distance to nearest road for each .1° grid cell centroid calculated using ESRI ArcMap 10.0

12. Distance to coast

Distance to nearest coastal point for each .1° grid cell centroid calculated using ESRI ArcMap 10.0

13. Travel time to nearest city>50,000 population: Travel time to major cities: A global map of Accessibility: <http://bioval.jrc.ec.europa.eu/products/gam/index.htm>

Resolution: 30 arc seconds

Projection: Lat/long

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation. Nelson, A. 2008. Estimated travel time to the nearest city of 50,000 or more people in year 2000. Global Environment Monitoring Unit - Joint Research Centre of the European Commission, Ispra Italy.

14. Forested land opportunity cost: Forest Carbon Index – Price Geography

<http://www.forestcarbonindex.org/maps.html>

Resampled to 0.1° lat/long projection using ESRI ArcMap 10.0

Citation: RFF (Resources for the Future and Climate Advisors). 2011. The Geography of Forests in Climate Solutions: Price Geography. <http://www.forestcarbonindex.org/maps.html>