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Potential Forest Loss and Biodiversity Risks from Road Improvement in Lao PDR

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Abstract

This paper develops and applies a spatial econometric model that links road upgrading to forest clearing and biodiversity loss in the Lao People's Democratic Republic. The paper uses 500-meter cells to estimate the relationship between the rate of forest clearing in a cell and its distance to the closest point on the nearest road link, the quality of that link, the cell's legal protection status, transport cost to the nearest urban center, the agricultural opportunity value of the land, and terrain elevation. The parameter estimates are all robust, with the expected signs and very high statistical significance. The paper highlights the results that measure the impact of improved road quality on forest clearing through shorter transport times to market and lower vehicle maintenance costs. The estimated response parameters and a composite biodiversity indicator are used to compute an index of expected biodiversity loss from road upgrading in each 500meter cell. The results identify areas in the Lao People's Democratic Republic where high expected biodiversity loss may warrant additional protection as road upgrading continues. This analysis will help policy makers in the country to weigh context-specific trade-offs between development and conservation objectives associated with road improvement.

Potential Forest Loss and Biodiversity Risks from Road Improvement in Lao PDR

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1. Introduction

Protected-area strategies seek to conserve biodiversity in tropical forests by restricting infrastructure development in legally-demarcated zones. However, conflicts can arise when forested areas have significant agricultural potential. Within conservation areas, regulatory enforcement may be weakened by dominant economic interests. And some areas with high biodiversity value may be left unprotected so that development can proceed. By implication, both development and conservation may be hindered by a dichotomous policy regime that treats large areas as either completely protected or completely open for development. In reality, valuable economic and ecological resources have non-uniform, overlapping spatial distributions. Policy makers in the Lao People's Democratic Republic should therefore be equipped to weigh context-specific trade-offs between development and conservation objectives. This paper seeks to contribute by focusing on the trade-offs associated with road improvement. We develop and apply a high-resolution spatial model of road improvement impacts that includes both ecological risks and the economics of forest clearing.

The remainder of the paper is organized as follows. Section 2 reviews prior empirical research on the economics of forest clearing globally. In Section 3, we motivate our exercise with a theoretical economic model of road improvement and deforestation. Sections 2 and 3 largely replicate the discussion in Dasgupta and Wheeler (2016). Section 4 describes our spatially-formatted database for Lao PDR, while Section 5 specifies and estimates a deforestation model that incorporates the impact of road improvement. In Section 6, we prepare for the assessment of ecological impacts by developing a composite high-resolution ecological risk indicator for Lao PDR. Section 7 uses the results of Sections 5 and 6 to develop high-resolution estimates of potential ecological risks from a national road improvement program in Lao PDR. Section 8 summarizes and concludes the paper.

2. Prior Research

Empirical research has provided many useful insights about the determinants of forest clearing. The results are generally consistent with an economic model in which the conversion of forested land varies with potential profitability. Nelson and Chomitz (2009) and Rudel et al. (2009) have studied this relationship across countries over multi-year intervals. Within countries, numerous econometric studies have estimated the impact of economic, social and geographic drivers on deforestation 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 for extended periods (e.g. Zikri (2009) for Indonesia; Ewers et al. (2008) for Brazil).

While econometric work on long-run deforestation drivers is well-advanced, previous data problems limited treatments of economic dynamics to theoretical work and simulation. Arcanda et al. (2008) and others 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.

Recently, the advent of monthly and annual remote sensing databases has led to the first spatial estimation exercises that explicitly incorporate economic dynamics (Wheeler et al., 2011; Dasgupta et al., 2014). Direct impact studies in Latin America using the new databases have

included high-resolution work on new road construction and deforestation in Brazil, where satellite monitoring has been available for a longer period (Laurance et al., 2009) and Bolivia, Panama, Paraguay and Peru (Reymondin et al., 2013).

More recently, Li et al. (2015) have investigated the potential impact of decreased travel time from improvement of road links in the Democratic Republic of Congo, but their cross-sectional analysis employs land use information (JRC 2003) that predates the new high-resolution satellite data. Damania et al. (2018) and Dasgupta and Wheeler (2016) have advanced the state of the art by estimating the potential impact of road upgrading on forest clearing and biodiversity in Bolivia, Cameroon, Myanmar and eight Congo Basin countries. Their deforestation models incorporate the latest high-resolution satellite data on forest cover changes, as well as quality estimates for specific links in the regional road system. They also create a biodiversity threat index that combines and synthesizes several measures of potential biodiversity loss. This paper builds on the work of Damania et al., (2018) and Dasgupta and Wheeler (2016), while extending it with a significantly-broader index of potential biodiversity loss and explicit adjustment of biodiversity risk assessment to incorporate the latest information about remaining forested areas.

3. Modeling the Economics of Road Improvement and Deforestation

From a formal analytical perspective, this research treats road improvement as a problem of competitive selection among corridors that traverse the same region. The corridors differ in length, construction cost conditions, biodiversity value and potential agricultural income. The optimum corridor choice reflects maximization of a social utility function that values both income and biodiversity, subject to a fixed budget constraint, feasible road quality improvement in each corridor (reflecting the budget constraint), and the corridor-specific impacts of road quality

improvement on potential biodiversity loss, expected income growth in the corridor, and expected income growth from increased trade between areas connected by the corridor.

We motivate the following econometric analysis with a model that specifies the basic determinants of road improvement impacts and explores their economic and ecological dimensions.[1] For expositional clarity and simplicity, we use the Cobb-Douglas (constant-elasticity) specification for all profit and cost functions. This specification is linear in the logs of equation variables and is a first-order approximation to more general specifications (CES, translog, etc.). To simplify the theoretical analysis of alternatives, we assume a constant road improvement budget. Applied assessments of road improvement alternatives might also consider cases where road quality is held constant and improvement expenditures differ because corridors differ in length. In such cases, estimated improvement costs would be subtracted from estimated income gains to provide the appropriate comparison.

3.1 Interregional Trade

We specify the economic value of trade between areas connected by a road corridor with a standard gravity model, augmented by a measure of road quality. For prior applications of this approach to overland trade expansion, see Damania et al., (2018), Dasgupta and Wheeler (2016), and Buys, Deichmann and Wheeler (2010).

$$(1)\ T_{ij} = \alpha_0\, E_i^{\alpha_1} E_j^{\alpha_2}\, d_{ij}^{-\alpha_3} q_{ij}^{\alpha_4}$$

where $\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4 > 0$

T_{ij} = Value of trade between areas i and j
E_i, E_j = Economic scale of areas i and j
d_{ij} = Road distance between areas i and j
q_{ij} = Quality of the road linking areas i and j ($0 \le q \le 1$, where $0 \rightarrow$ forest track and $1 \rightarrow$ paved 1st class road)

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[1] The theoretical model in this section was first developed by one of the co-authors (Wheeler) in collaborative work with Richard Damania on road upgrading and forest clearing in the Congo Basin countries (Damania et al., 2018). Many thanks to Richard for his insights and suggestions.

An improvement in road quality (q) lowers transport costs and increases the potential profitability of agricultural production in the road corridor. The budget for maintaining a particular road quality level is given by:

(2) $B = \gamma_0 q^{\gamma_1} d \quad (\gamma_1 > 1)$

For a fixed road quality budget B:

(3) $q = [\frac{B}{\gamma_0}]^{\frac{1}{\gamma_1}} d^{-\frac{1}{\gamma_1}}$

In (3), given a fixed road quality budget, road quality declines with road length. The rate of decline depends on the cost elasticity of road quality. Substituting (3) into (1) and simplifying, an increase in the road improvement budget ($B_1 \rightarrow B_2$) has the following impact on trade between areas i and j:

(4) $\frac{T_{ij2}}{T_{ij1}} = [\frac{B_2}{B_1}]^{\frac{\alpha_4}{\gamma_1}}$

The interpretation of (4) is straightforward: Trade between areas i and j will expand more or less proportionately with the road improvement budget, depending upon whether the road quality elasticity of trade is greater than or less than the cost elasticity of road quality.

3.2 Local Profitability and Forest Clearing

An improvement in road quality lowers transport costs and increases the expected profitability of agricultural production in a road corridor. The expected profitability of agricultural production increases with the size of a cleared parcel, which is determined by the distance of the forest clearing limit from the road. With both factors taken into account, the expected profit function for each unit of road frontage is:

(5) $\pi = \beta_0 v^{\beta_1} q_{ij}^{\beta_2} h^{\beta_3}$

where $\beta_0, \beta_1, \beta_2 > 0, 0 < \beta_3 \leq 1$

   π = Potential profit from land clearing

   v = Potential agricultural value per hectare

   h = Distance of forest-clearing limit from the road

The proprietor of each road-front parcel also confronts incremental forest clearing costs that are constant or increasing with distance from the road and, for agricultural production, incremental commodity transport costs that increase with distance from the road. The proprietor's composite cost function is:

(6) $C = \delta_0 h^{\delta_1}$ $(\delta_1 > 1)$

With (5) and (6) specified as present values, the optimal clearing distance from the road is determined by the equality of marginal expected profits and clearing costs. Taking appropriate derivatives, substituting and simplifying, the optimal clearing distance is given by:

(7) $h^* = \theta B^{(\frac{\mu}{\delta_1 - \beta_3})} v^{(\frac{\beta_1}{\delta_1 - \beta_3})} d^{-(\frac{\mu}{\delta_1 - \beta_3})}$

where $\mu = \beta_2/\gamma_1$, $\delta_1 - \beta_3 > 0$ (from (5) and (6)) and θ is a composite of equation constants.

In (7), the composite elasticities of B, v and d are positive, positive and negative, respectively. Responsiveness increases in each case as the difference narrows between the cost and profit elasticities of forest clearing (δ_1 and β_3). The responsiveness of forest clearing to greater spending on road quality and greater road distance increases with the ratio of the profit and cost elasticities of road quality.

Appropriate substitution and simplification yield the following expression for total profit in the road corridor:

(8) $\Pi = 2d\pi(h^*) = PB^{\rho\mu} v^{\rho\beta_1} d^{1-\rho\mu}$

where P is a composite of equation constants and $\rho = \frac{1+\beta_3}{\delta_1 - \beta_3}$ (> 1).

In (8), total expected profits rise less than proportionally with road distance, since expected profits for each roadside land parcel fall as road distance increases. The sign of the distance elasticity in (8) is ambiguous, since ρμ can be greater or less than one. In the former case, total profits will actually fall as road distance increases. From (8), an increase in the road improvement budget ($B_1 \rightarrow B_2$) has the following impact on total profits in a road corridor:

$$(9)\ \frac{\Pi_2}{\Pi_1} = [\frac{B_2}{B_1}]^{\rho\mu}$$

In (9), total road corridor profits increase more or less proportionately with the road quality budget, depending upon whether ρμ is greater or less than one. The overall interpretation of (9) is as follows: For a road corridor, the responsiveness of total profits to an increase in the road quality budget is positively related to the ratio of profit and cost elasticities of road quality, positively related to the profit elasticity of forest clearing, and negatively related to the difference between the cost and profit elasticities of forest clearing.

3.3 Biodiversity Loss

Substituting from (7), total biodiversity loss in a road corridor is given by:

$$(10)\ L = 2d\varepsilon h^* = 2\varepsilon\theta B^{(\frac{\mu}{\delta_1-\beta_3})} v^{(\frac{\beta_1}{\delta_1-\beta_3})} d^{1-(\frac{\mu}{\delta_1-\beta_3})}$$

where ε = measured biodiversity intensity.

In (10), the relationship between total biodiversity loss and road distance depends on whether the ratio of the profit and cost elasticities of road quality is greater than the difference between the cost and profit elasticities of forest clearing. If this is the case (given a fixed budget for road quality), total biodiversity loss will decline with road distance. If the converse is true, increasing road distance will increase biodiversity loss.

From (10), the relationship between a road budget increase and total biodiversity loss is given by:

(11) $\frac{L_2}{L_1} = [\frac{B_2}{B_1}]^{(\frac{\mu}{\delta_1 - \beta_3})}$.

As above, biodiversity loss will increase more than proportionately with a road budget increase if the ratio of profit and cost elasticities of road quality is greater than the difference between the cost and profit elasticities of forest clearing.

For a fixed road quality budget, the relative profit and biodiversity loss equations for two competitive road corridors (A and B) are as follows:

(12) $\frac{\Pi_A}{\Pi_B} = [\frac{v_A}{v_B}]^{\rho \beta_1} [\frac{d_A}{d_B}]^{1-\rho\mu}$

(13) $\frac{L_A}{L_B} = \frac{\varepsilon_A}{\varepsilon_B} [\frac{v_A}{v_B}]^{(\frac{\beta_1}{\delta_1 - \beta_3})} [\frac{d_A}{d_B}]^{1-(\frac{\mu}{\delta_1 - \beta_3})}$

Ceteris paribus (i.e., for identical road budgets and biodiversity intensities), the corridor with greater potential agricultural value per hectare will have both higher total profits and greater total biodiversity loss. The effects of road distance are more complex for two reasons. First:

(14) $\rho\mu - \frac{\mu}{\delta_1 - \beta_3} = \frac{1 + \beta_3}{\delta_1 - \beta_3}\mu - \frac{1}{\delta_1 - \beta_3}\mu = \frac{\beta_3}{\delta_1 - \beta_3}\mu$ (> 0)

Given (14), equations (12) and (13) incorporate three possibilities. Let $\eta_1 = \rho\mu$ and $\eta_2 = \mu/(\delta_1 - \beta_3)$. If η_1 and η_2 are both less than one, the corridor with the longer road will have greater total profits and greater biodiversity loss. If η_1 and η_2 are both greater than one, the corridor with the longer road will have lower profits and lower biodiversity loss. In the third possible case -- η_1 > 1 and η_2 < 1 -- the corridor with the *shorter* road will be favored unambiguously because it will have higher profits and lower biodiversity loss. It is important to note that this is a ceteris paribus result, since the corridor with the shorter road could have sufficiently greater biodiversity intensity to reverse the result. A complete calculation would also have to include consideration of trade-related regional income, which would favor the shorter road. Given the relatively complex set of

factors that affect these results, the impacts of road improvement on income gains, forest clearing and biodiversity loss seem likely to vary significantly across countries, and across regions within countries. In this paper, we focus on the forest clearing and biodiversity components of the problem.

4. Data

4.1 Road Networks

Table 1 and Figure 1 summarize 2015 road network information for Lao PDR in digital maps (shapefiles) provided by Delorme, Inc. As Table 1 shows, the maps identify 2,055 road network links. Network links are graded by status: primary roads (purple in Figure 1), secondary roads (red), and tertiary roads (orange).

Table 1: Delorme road links by network status: Lao PDR

Road Type	Links
Primary	370
Secondary	309
Tertiary	1,376
Total	2,055

Figure 1: Lao PDR road networks
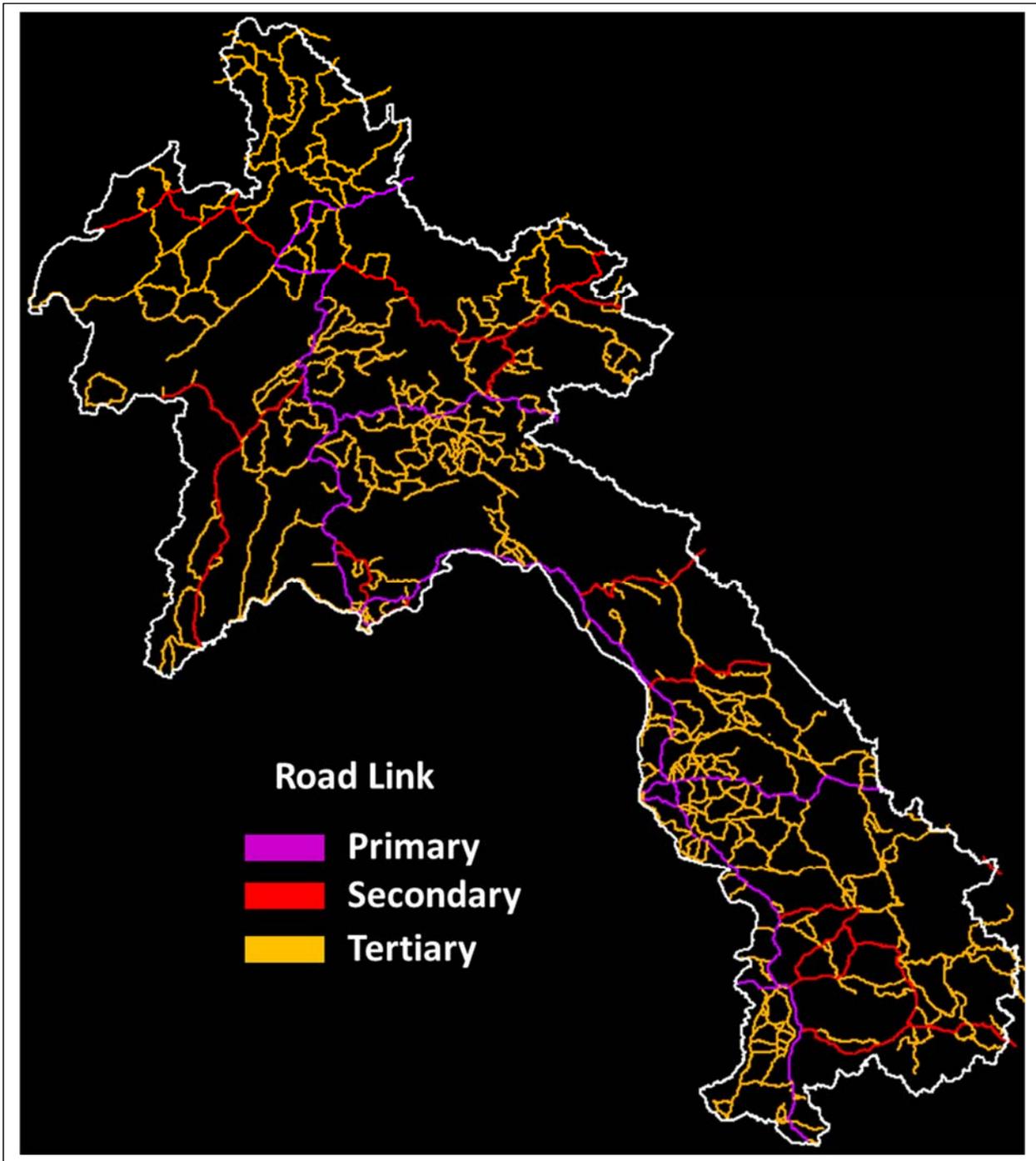
4.2 Forest Clearing

Hansen et al. (2013) publish annual high-resolution estimates of global forest clearing. The data are currently available at 30 m spatial resolution for 2001-2016. We use the Hansen estimates to compute forest clearing rates through 2016 in 500 m cells.[2,3] Figures 2 and 3 display our results for Lao PDR in 2000 and 2016, aggregated to 0.1-degree cells for ease of interpretation. Each cell is color coded by total percent cleared in the relevant year. Figure 2 (2000) reveals an initial pattern of forest clearing in road corridors that becomes much more pronounced in Figure 3 (2016), particularly in areas of high road network density.

5. Estimation of the Forest Clearing Model

The estimation exercise in this paper draws on the insights of previous research and the theoretical model in Section 3 to incorporate five critical determinants of forest clearing in road corridors: distance from the road, road quality, legal protection status, transport time to the nearest market center and terrain elevation. Following Damania et al. (2018) and Dasgupta and Wheeler (2016), we extend previous work on road transport cost and deforestation by introducing explicit estimation of road quality effects.

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[2] We use the 500 m approximation for expositional convenience. Our cell sides are .005 decimal degrees in length. This translates to 556.6 meters on a side, yielding cell areas of 309,804 square meters or 30.98 hectares. We produce Hansen estimates at .005-degree resolution by resampling Hansen 30 m raster values (1 if clearing occurred from 2001 to 2016; 0 otherwise).

[3] Our estimate also incorporates the Hansen 30 m estimates of tree cover in 2000.

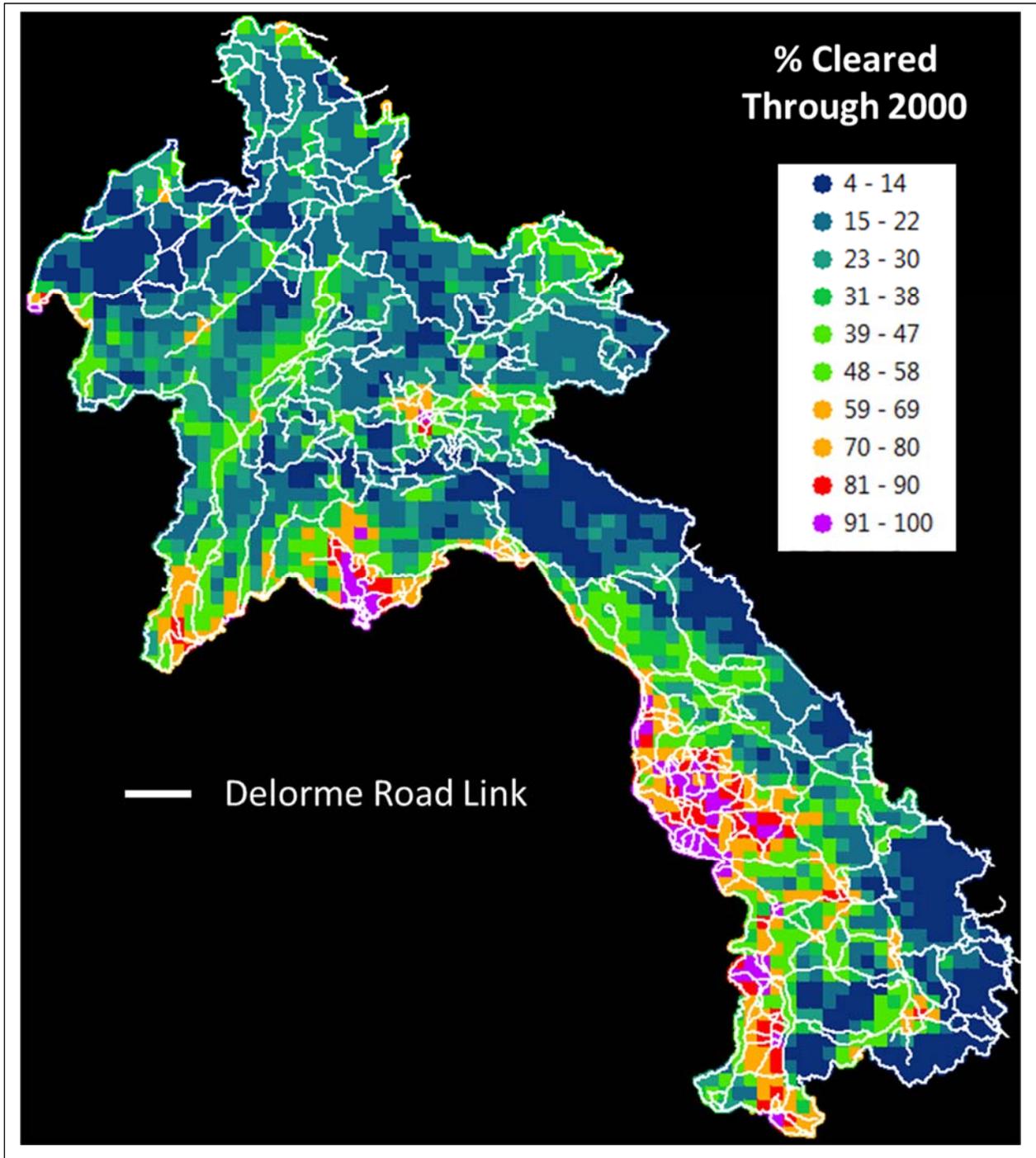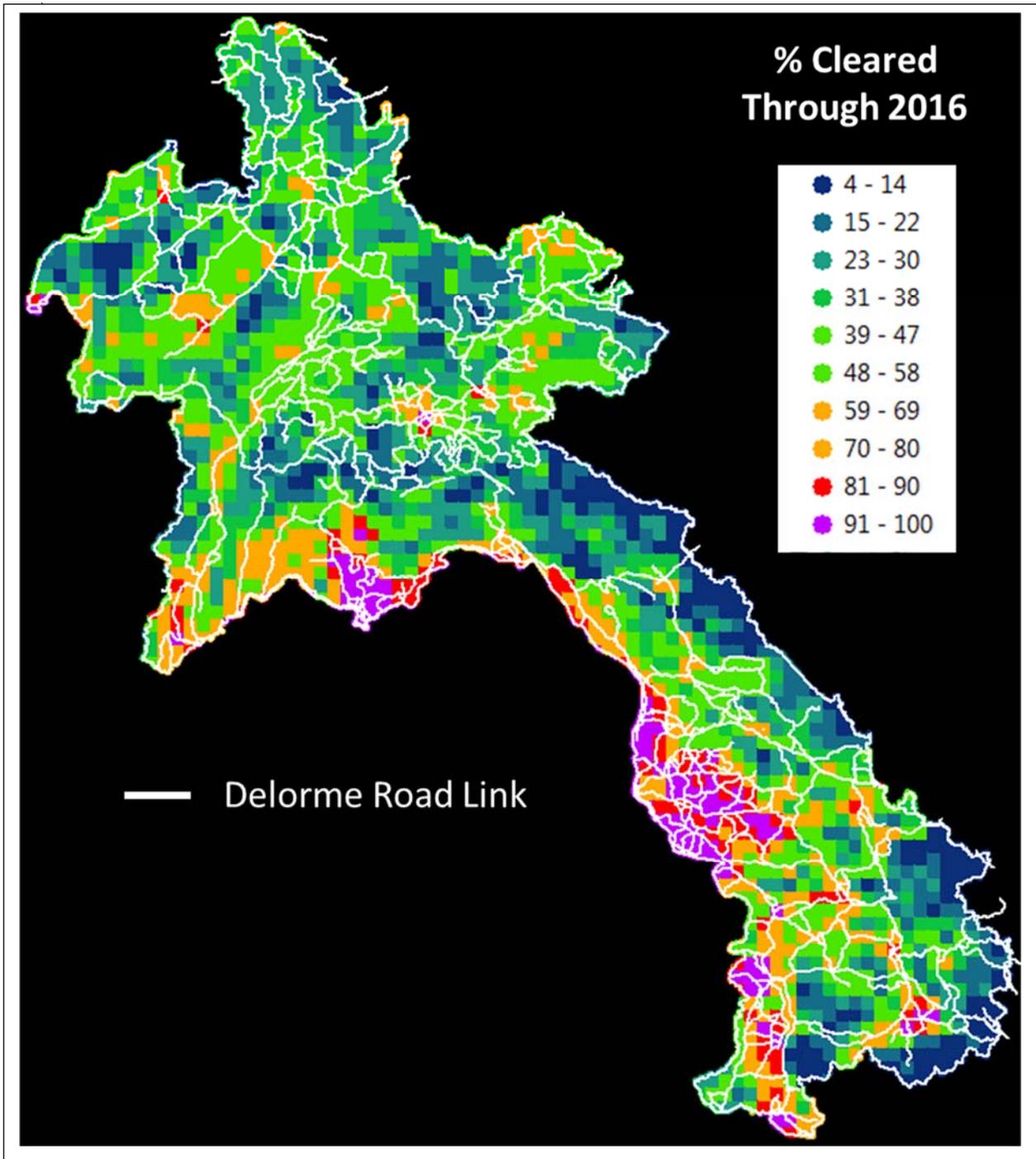**Figure 2: Road network and forest clearing in Lao PDR, 2000**

Figure 3: Road network and forest clearing in Lao PDR, 2016

5.1 Model Specification

We specify our estimation model as follows.

(15) $c_i = \beta_0 + \beta_1 \ln d_i + \beta_2 q_2 + \beta_3 q_3 + \beta_4 p_i + \beta_5 t_i + \beta_6 a_i + \beta_7 h_i + \varepsilon_i$

Expected signs: $\beta_1, \beta_4, \beta_5, \beta_7 < 0$; $\beta_3 < \beta_2 < 0$; $\beta_6 > 0$

where

c_i = Cumulative percent cleared in 2016, cell i
d_i = Distance of cell i from nearest road segment
q_k = Quality dummy variable for nearest road segment
    [q_2: secondary road; q_3: tertiary road] (q_1 excluded (effect absorbed in the
    regression constant) to prevent total collinearity)
p_i = Legal protection status of cell i [1 if protected; 0 otherwise]
t_i = Transport time from cell i to the nearest urban market center
a_i = Agricultural opportunity value of land in cell i
h_i = Elevation of cell i
ε_i = Random error term

A priori, we expect the impact on forest clearing to be negative for distance from the nearest road ($\beta_1 < 0$); decreasing as road quality declines ($\beta_3 < \beta_2 < 0$); negative for legally-protected areas ($\beta_4 < 0$); negative for transport distance to the nearest urban center ($\beta_5 < 0$), positive for the agricultural opportunity value of the land ($\beta_6 > 0$); and negative for more elevated terrain ($\beta_7 < 0$).

5.2 Variable Measures

Our data and sources are as follows.

Cumulative percent cleared, 2016: this incorporates two Hansen measures: percent cleared prior to 2001 and annual clearing from 2001 to 2016 (Hansen et al. (2013)). We produce estimates at .005-degree resolution by resampling Hansen 30 m raster values.

Distance from road segment: distance from the centroid of each cell to the nearest road segment, calculated in ArcGIS 10.

Road quality: proxied by primary, secondary or tertiary status assigned by Delorme (Table 1).

Legal protection status: 1 if the cell is in a protected area identified by the World Database on Protected Areas (WDPA); 0 otherwise. The WDPA shapefile has been downloaded from http://www.protectedplanet.net/.

Travel time: time from the cell centroid to the nearest urban center with a population of 50,000 or greater, as estimated by Uchida and Nelson (2009). Raster resolution: .0083 decimal degrees.

Agricultural opportunity value: mean value for a cell, calculated from the high-resolution global grid developed by Deveny et al. (2009). Raster resolution: .0025 decimal degrees.

Elevation: Lao PDR data extracted from the CGIAR-SRTM data set (3 arc-seconds (approximately 90 m) resolution), downloaded from http://srtm.csi.cgiar.org.

5.3 Estimation

For this exercise, we utilize an 11% random sample to minimize potential estimation bias and inconsistency produced by spatial autocorrelation among neighboring cells.[4] The dependent variable is continuously distributed in the range [0,1], so the appropriate estimator is fractional logit.[5] Table 2 presents our results, which are uniformly robust: All parameter signs match our prior expectations, and all have high statistical significance. For 500 m Hansen cells, forest clearing declines with distance from the nearest road segment, transport time to the nearest urban center and elevation. We have excluded Delorme primary status, so the results for road quality dummy variables should be interpreted as deviations from the impact of primary road segments: Ceteris paribus, secondary roads have lower impact on forest clearing than primary roads, and the impact of tertiary roads is lower still. As expected, clearing is greater on land with higher agricultural opportunity value. Our result for protected status is striking and holds independent

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[4] The full data set contains 795,072 observations for Lao PDR, georeferenced by centroids of Hansen-resampled .005-degree cells. We randomly select 100,000 observations from the data set. After elimination of rows with missing values for at least one regression variable, the regression data set contains 90,330 observations -- 11.4% of the full data set.

[5] We employ the Stata estimator glm [link(logit); family(binomial); vce(robust)].

interest: Forest clearing is much lower in protected areas than the other model variables would predict, and the effect has high statistical significance.

Table 2: Regression results: Forest clearing in Lao PDR

Dependent variable: Cumulative percent cleared, 2016

Regression variables:

Log distance from nearest road segment	-0.208 (63.30)**
Secondary road segment	-0.151 (10.67)**
Tertiary road segment	-0.224 (18.65)**
Legally protected	-0.720 (70.17)**
Transport time	-0.001 (36.26)**
Agricultural opportunity value	0.003 (52.72)**
Elevation	-0.001 (84.07)**
Constant	0.967 (68.68)**
Observations	90,330

Robust t statistics in parentheses
* significant at 5%; ** significant at 1%

5.4 Implications for Forest Clearing

To assess the implications of our results, we upgrade all secondary and tertiary road links to primary status and predict the resulting changes in clearing for all Hansen cells in our database. Figures 4 and 5 display predicted cumulative clearing and the change from 2016, respectively. Predicted impacts vary widely, with little or no change in areas far from the Delorme road network[6]

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[6] The econometric results for log (distance from road) in Table 2 quantify a continuous relationship, so upgrading secondary and tertiary roads will have small predicted effects in areas that are relatively far from those roads.

and areas dominated by roads that already have primary status. Figure 5 shows that the largest predicted changes in forest clearing are concentrated in northern Lao PDR, with the largest clusters visible in the northwest, southwest and eastern parts of the northern region.

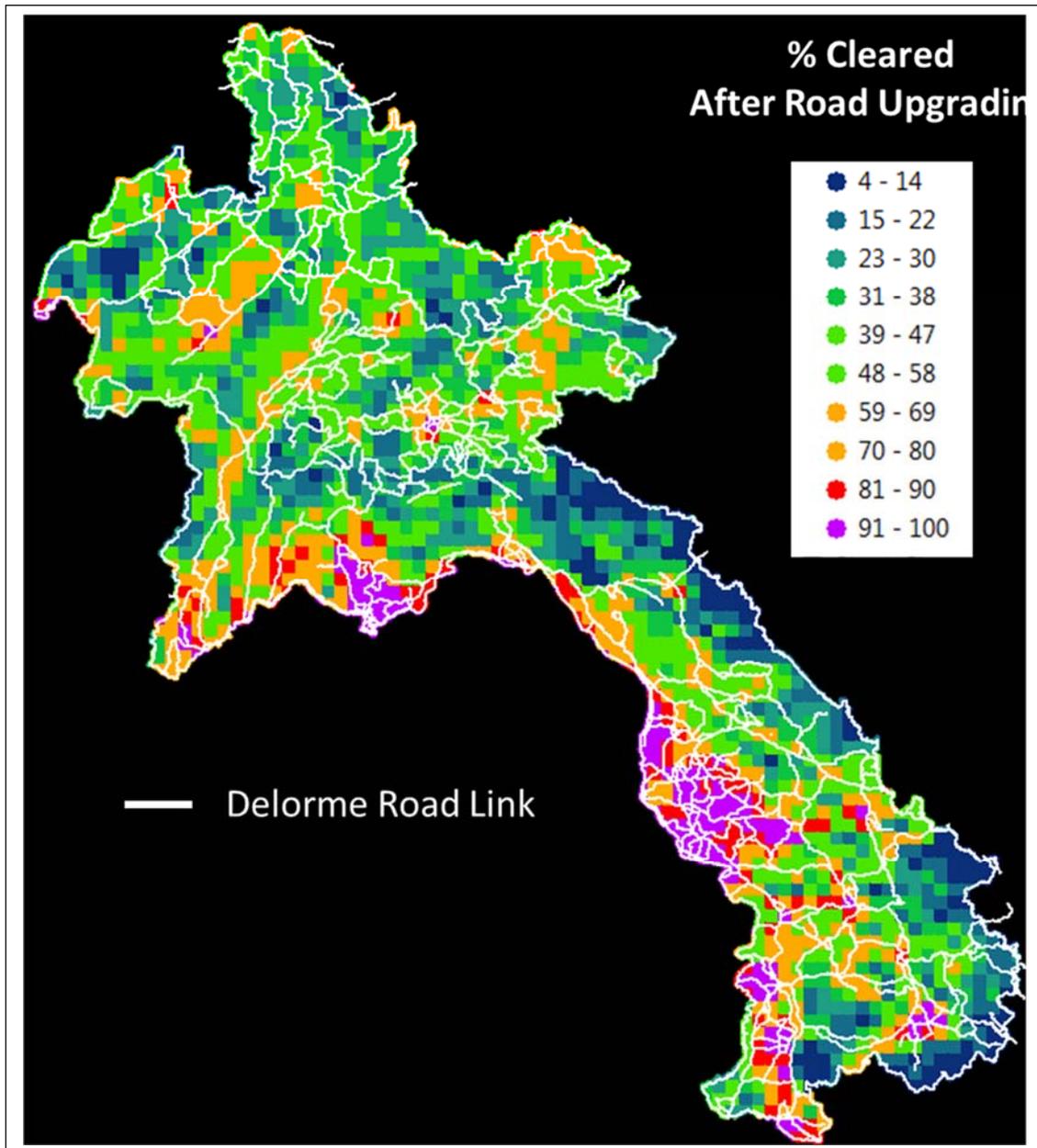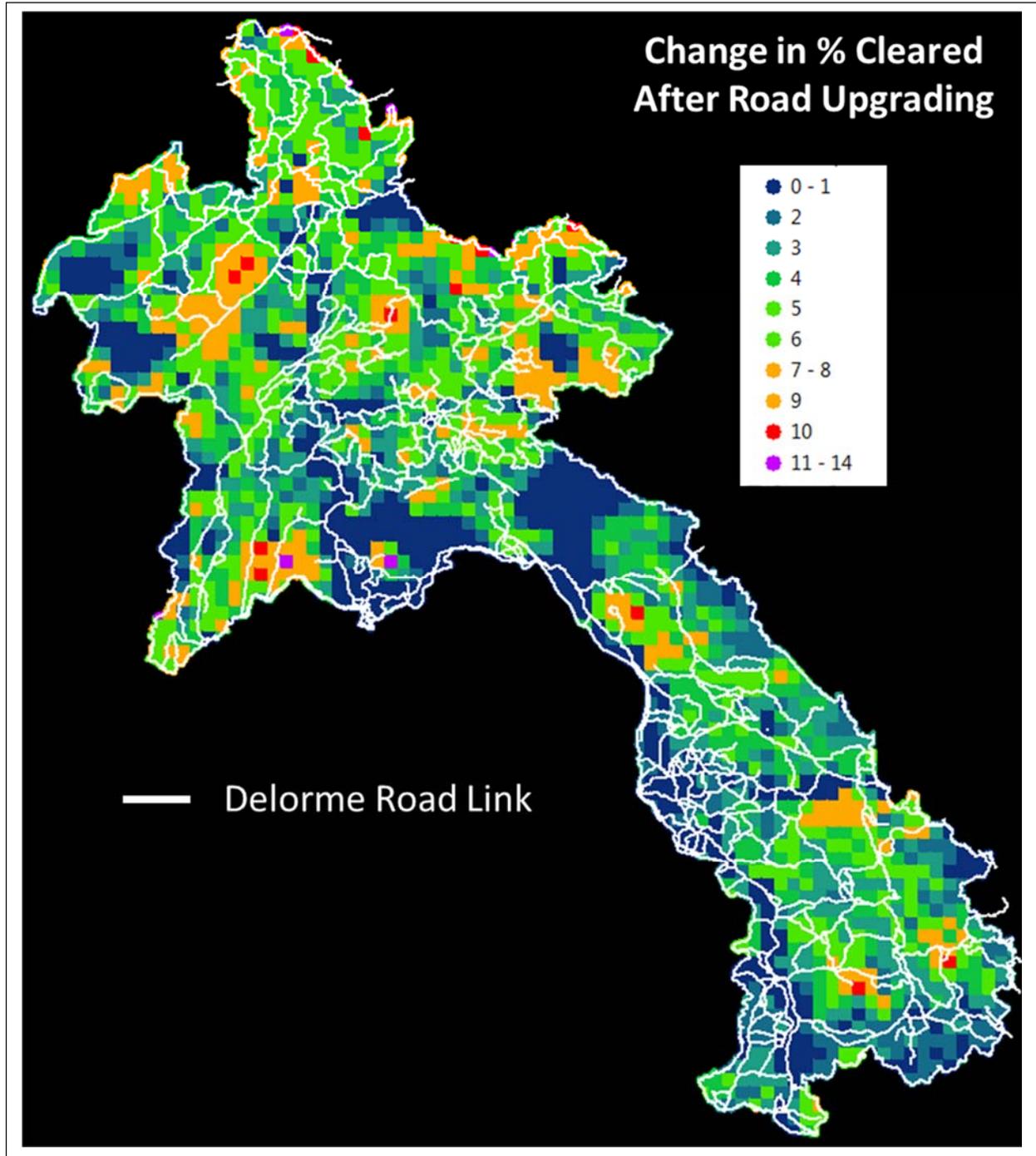**Figure 4: Cumulative forest clearing after road upgrading**

Figure 5: Forest clearing attributable to road upgrading

6. Incorporating Biodiversity

Drawing on a new World Bank database, we develop a multidimensional biodiversity indicator for Lao PDR to identify concentrations of diverse species and their vulnerability to encroachment and habitat loss. The database incorporates information from thousands of digital range maps (shapefiles) provided by the International Union for the Conservation of Nature (IUCN) and BirdLife International. We also incorporate ecoregion maps provided by WWF International. We use GIS overlays to compute our biodiversity indicator for each Hansen cell in our forest clearing database. Our approach follows the methodology developed in Dasgupta and Wheeler (2016), but draws on the new World Bank database to incorporate many more dimensions of vulnerability and risk. Our approach incorporates separate measures for amphibians, mammals, reptiles, birds and WWF ecoregions.

6.1 Species Density

We measure species density as the species count for each 500 m Hansen cell.

6.2 Species Vulnerability

Species density provides critical information for assessing ecological risks, but at least two other elements are needed:

(1) *Geographic vulnerability*, which can be proxied by *endemicity*: the proportion of each species' range that lies within each cell. Species that reside in very few cells may be particularly vulnerable to habitat encroachment. For this exercise, endemicity treats all species equally at the national level, since each species has a total count of 1. Total endemicity for each cell -- the sum of its species endemicity measures -- assigns higher values to cells inhabited by species whose ranges are relatively limited. By implication, forest clearing in higher-value cells may be particularly destructive for remaining critical habitat.

(2) **A measure of *extinction risk*** that adds the insights of the international scientific community. We convert IUCN Red List status codes to extinction probabilities using the methodology of Mooers et al. (2008).[7] For species indicator construction, we normalize these probabilities so that a weight of 1.0 is assigned to species in the highest category (Critically Endangered). Table 3 tabulates conversions from Red List codes to normalized species weights, using four probability assignments. Three employ IUCN estimates to derive measures of extinction probability over the next 50, 100 and 500 years. The fourth draws on Isaac et al. (2007), who combine a direct extinction risk measure with a measure of each species' isolation on a phylogenetic tree.[8]

Table 3: Normalized species aggregation weights[a]

IUCN Code	Status	Normalized Extinction Probabilities			
			IUCN: Future Years		
		Isaac[b]	50	100	500
CR	Critically Endangered	1.00000	1.00000	1.00000	1.00000
EN	Endangered	0.50000	0.43299	0.66770	0.99600
VU	Vulnerable	0.25000	0.05155	0.10010	0.39000
NT	Near Threatened	0.12500	0.00412	0.01000	0.02000
LC	Least Concern	0.06250	0.00005	0.00010	0.00050
	Rounded Weight Ratios				
	CR:EN	2	2	1	1
	CR:VU	4	19	10	3
	CR:NT	8	243	100	50
	CR:LC	16	20,000	10,000	2,000

[a] Data source: Mooers et al. (2008).
[b] From calculations by Mooers et al., based on Isaac et al. (2007).

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[7] The IUCN's current classification categories are Critically Endangered, Endangered, Vulnerable, Near Threatened and Least Concern.

[8] A phylogenetic tree is a branching tree diagram that traces the evolutionary descent of different species from a common ancestor. Species in sparse (isolated) branches of a phylogenetic tree are relatively unique, since they share common descent patterns with fewer other species.

Table 3 shows that Isaac's inclusion of the phylogenetic isolation factor changes the weight ratios substantially, particularly for species in the lowest threat category (Least Concern). We explore the implications for hypothetical areas A and B in Table 4. A is populated by only 2 species, both rated as Critically Endangered. B is populated by 20,000 species, but all are rated as of Least Concern. Our extinction risk indicator for each area is the sum of normalized extinction probabilities for resident species. Assignment of weights for Mooers' IUCN-derived 50-year extinction probabilities yields a total risk indicator of 2 for A -- twice the total for B, because each Critically Endangered species is weight-equivalent to 20,000 Least Concern species. In contrast, assignment of the Isaac weights yields an overall risk rating for B (1,250) that is 625 times greater than the rating for A (2), because each Critically Endangered Species is weight-equivalent to 16 species of Least Concern. The other two cases are intermediate, but far closer to the 50-year IUCN case.

Table 4: Implications of alternative weighting schemes

Area	Species Count	Status (Uniform Within Areas)	Total Scores			
				IUCN Extinction Probabilities: Future Years		
			Isaac	50	100	500
A	2	CR	2	2	2	2
B	20,000	LC	1,250	1	2	10

6.3 Biome Vulnerability

Measures based on animal species alone provide an incomplete accounting of biodiversity. A more complete measure would incorporate plants and insects, using indices similar to those we have developed for animals. Although no such indices exist at the requisite geographic scale, WWF has provided a first approximation by segmenting the world into 825 terrestrial ecoregions

(Figure 6). WWF defines an ecoregion as "a large unit of land or water containing a geographically distinct assemblage of species, natural communities, and environmental conditions."[9] Accordingly, we adopt the ecoregion as a general proxy for distinctive plant and inspect species, as well as animal species that are not represented in the range maps provided by IUCN and BirdLife International.

Our method for incorporating WWF ecoregions resembles our treatment of species endemicity. For this exercise, we identify all moist and dry forest ecoregions in Lao PDR. We compute the percent of total forest area in Lao PDR accounted for by each ecoregion. Then we compute its vulnerability index as the inverse of its area share and assign the appropriate index value to each cell. This accounting assigns high values to cells in smaller ecoregions, where clearing single cells may pose more significant threats to biome integrity.

6.4 A Composite Biodiversity Indicator

The example in Table 4 suggests that alternative vulnerability indicators may yield significantly different risk metrics. It is important for a vulnerability indicator methodology to accommodate different risk-weighting schemes in a consistent and plausible way. From the World Bank database, we obtain 50 spatially-formatted indicators:

Overall species indicators (8): total cell counts and total endemicity measures for four vertebrate classes: amphibians, mammals, reptiles and birds[10];

Species indicators by IUCN status (40): cell counts and endemicity measures for species within each vertebrate class in five IUCN risk status categories (per Table 3): CR (critically endangered), EN (endangered), VU (vulnerable), NT (near-threatened); and LC (least concern).

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[9] Complete information about the WWF terrestrial ecoregions is available online at http://wwf.panda.org/about_our_earth/ecoregions/.

[10] The total indicators include species in IUCN threat status class DD (data deficient).

Ecoregion indicators (2): Cell counts and endemicity measures for WWF ecoregions.

Figure 6: WWF Terrestrial Ecoregions
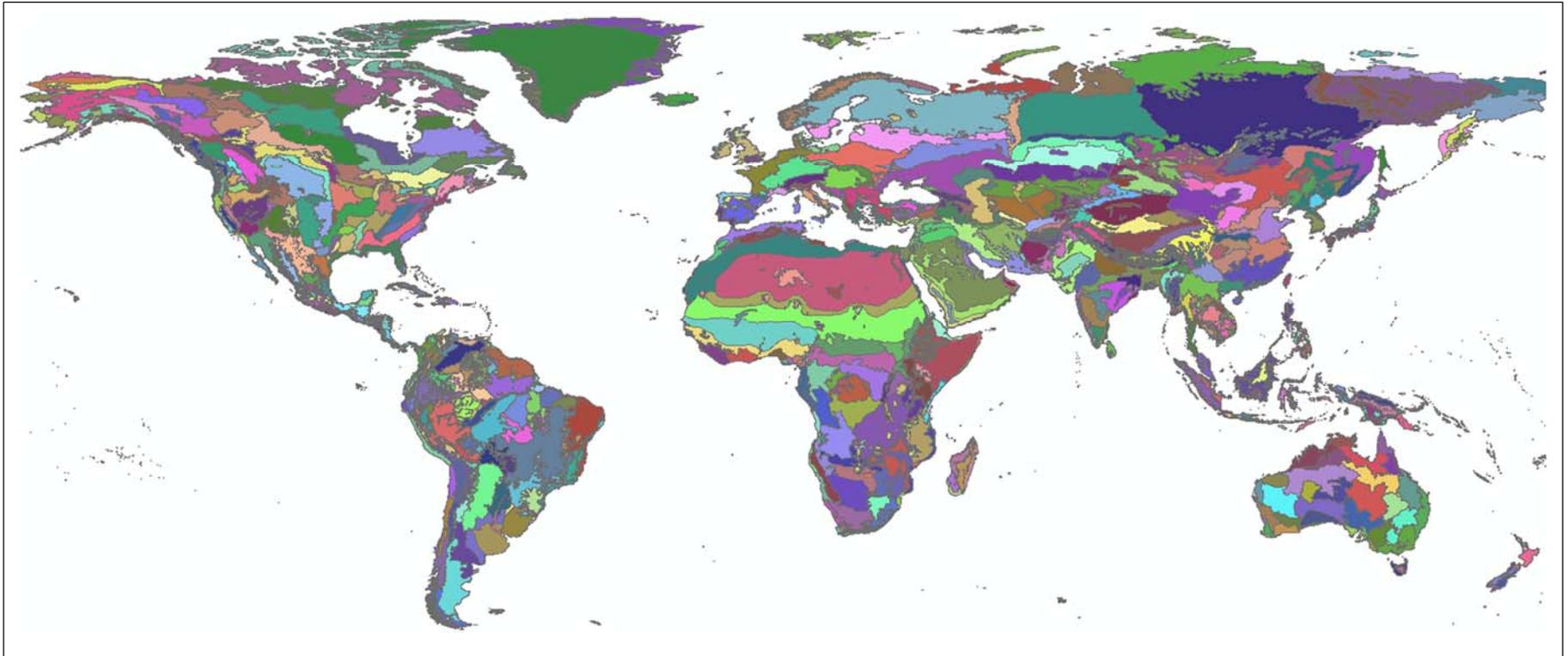
We recognize the potential diversity of stakeholder views about the relative importance of species-, ecoregion- and risk-related factors in this context. To accommodate diverse concerns, we adopt a conservative strategy for indicator construction. First, we divide each of our 50 indicators by its maximum value and multiply by 100 to create an index in the range 0-100. This ensures comparability in measurement. Then, for each 500 m Hansen cell in our database, we select the maximum value among 50 indices as our risk indicator. This ensures significant representation for the concerns of stakeholders whose focus may range from protection of critically-endangered amphibians to conservation of small Laotian biomes.

Figure 7 displays the geographic distribution of the resulting indicator, aggregated to 0.1 degree grid cells for ease of interpretation.[11] We have overlaid a province map of Lao PDR as a geographic reference. Figure 7 reveals a dominant wedge-shaped "axis" that narrows from the extreme northwest (where the highest indicator values are concentrated in Louang Namtha and Bokeo) to east-central Lao PDR (with the highest indicator values in Bolikhamxai and Khammouan). Large areas with high indicator values are also evident in Phôngsali, Oudômxai and Louangphrabang.

Figure 7 also reveals a much smaller "axis" in southeastern Lao PDR, with the highest indicator values concentrated in the eastern parts of Xékong and Attapu. Pockets of high indicator value are also visible in the southern frontier areas of Champasak and Attapu. These may well reflect small Laotian portions of ranges for species and/or ecoregions that extend into Cambodia. Our methodology focuses on Laotian national considerations, so the small Laotian portions of these regions/ecoregions would be assigned high endemicity value.

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[11] Our aggregative indicator is the maximum indicator value within each 0.1-degree grid cell.

6.5 Accounting for Forest Clearing

The composite biodiversity indicator in Figure 7 incorporates range and ecoregion maps that have not been explicitly adjusted for forest clearing. To provide a more accurate view of current biodiversity status, we combine the information sets reflected in Figures 3 and 7. Within each 500 m Hansen cell, we compute the product of the biodiversity indicator value and the estimated percent that remains forested in 2016. We aggregate to 0.1-degree grid cells by summing products within each aggregate cell and normalizing results so that the maximum cell value is 100. Comparison of the result in Figure 8 with Figure 7 shows that incorporation of forest clearing has a very significant effect: The previous, simple "wedge" geometry is replaced by a complex pattern with a broad distribution of the highest values. The highest-value areas in Figure 7 retain importance, but they are joined in Figure 8 by high-value clusters in Houaphan, Vientiane and Xaisômboun. In summary, the effect of incorporating forest clearing is wide dispersal of the remaining high-priority biodiversity conservation areas. In the clearing-adjusted map displayed by Figure 8, every Laotian province has clusters that rank among the highest-priority areas in Lao PDR.

Figure 7: Composite biodiversity indicator, Lao PDR

Composite Biodiversity
Indicator
[50 Sub-Indicators]

- 60.000000 - 74.375000
- 74.375001 - 79.615390
- 79.615391 - 83.461540
- 83.461541 - 85.769230
- 85.769231 - 88.269230
- 88.269231 - 90.961540
- 90.961541 - 93.461540
- 93.461541 - 95.625000
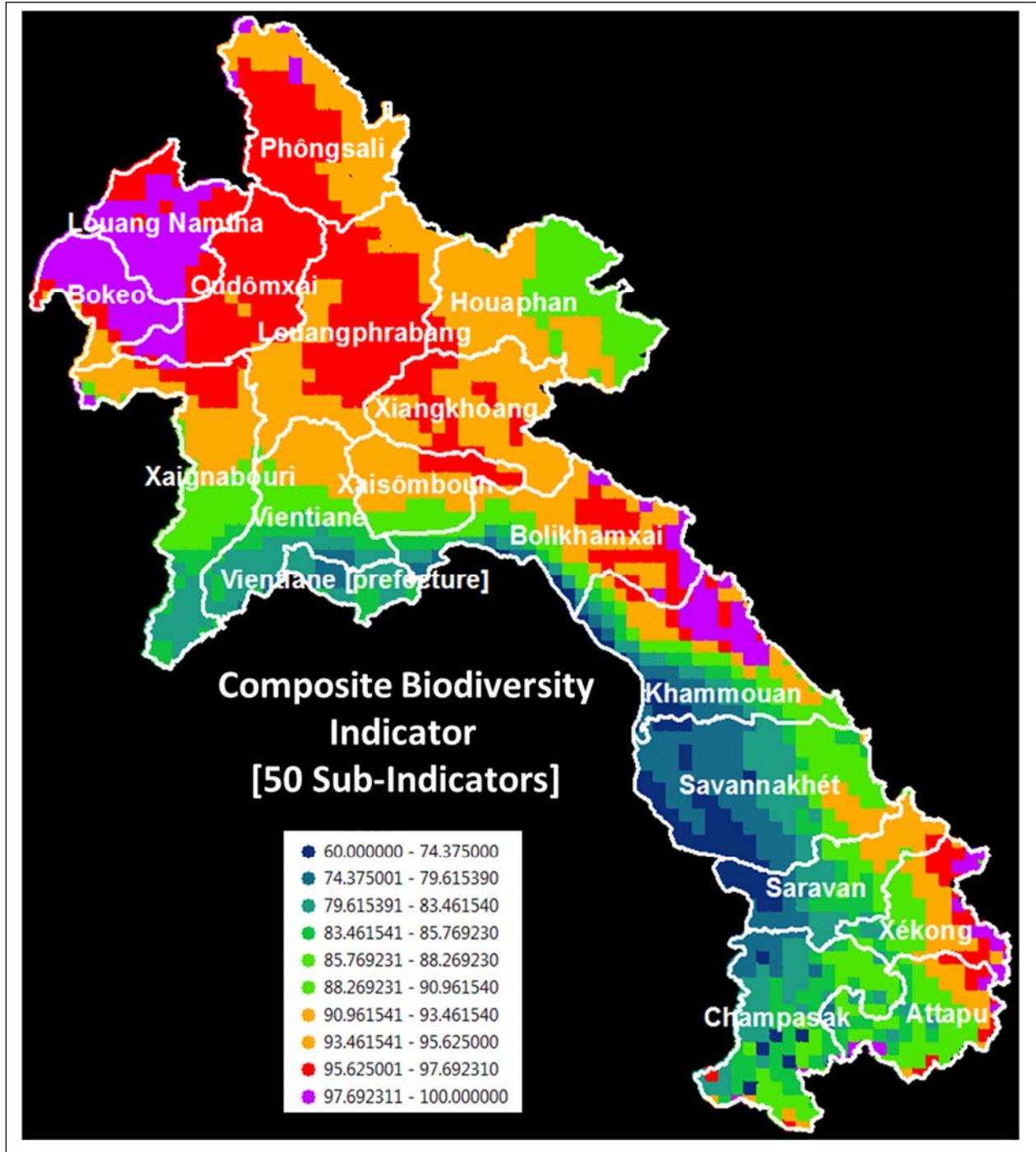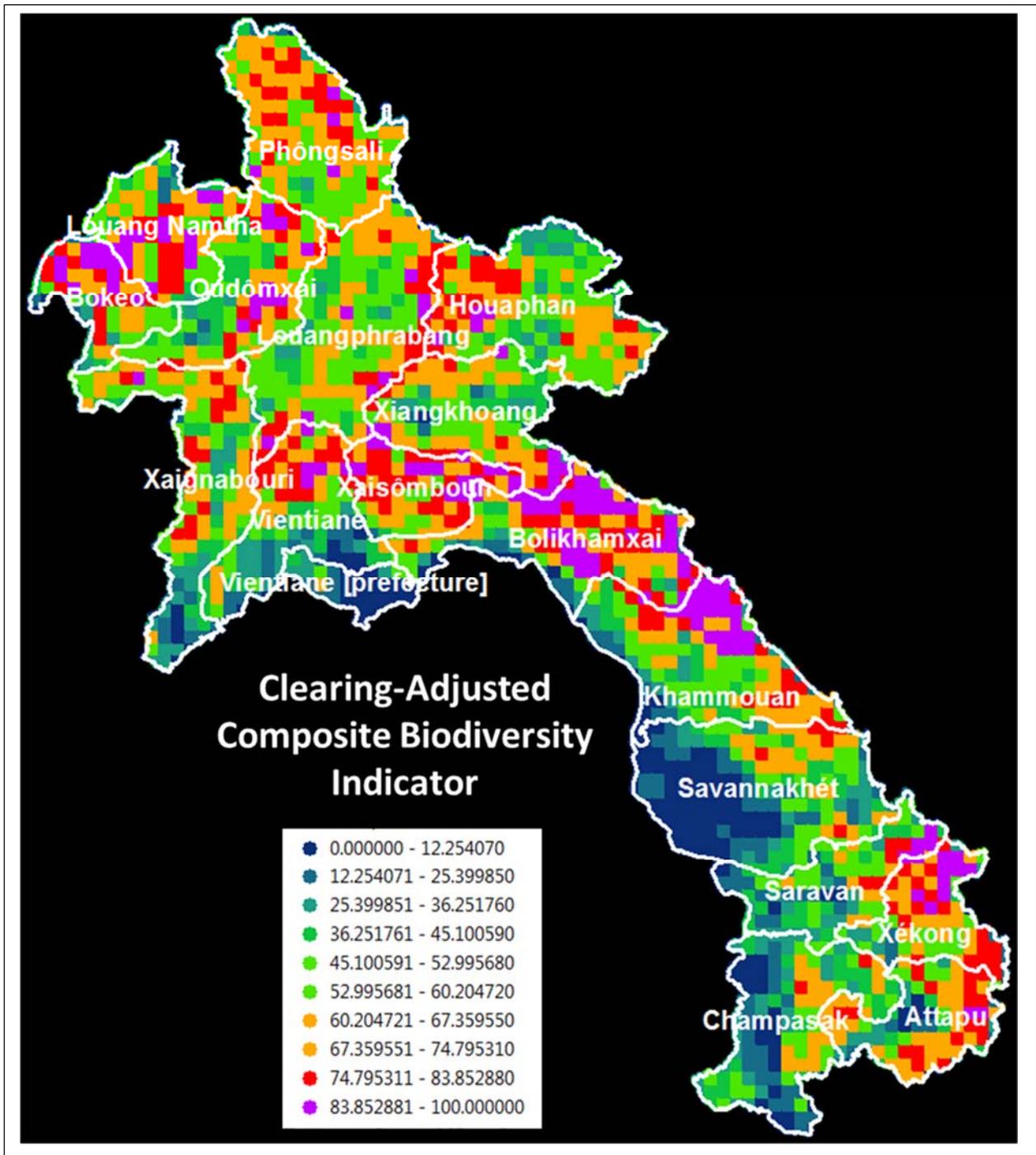- 95.625001 - 97.692310
- 97.692311 - 100.000000

Figure 8: Composite biodiversity indicator adjusted for forest clearing, 2016

7. Road Upgrading and Ecological Risk

We calculate expected biodiversity loss for a cell as the product of its previous-clearing-adjusted biodiversity indicator value (Figure 8) and the change in forest clearing induced by road upgrading (Figure 5). Figure 9 displays the geographic distribution of predicted biodiversity indicator values after road upgrading, while Figure 10 displays the change in indicator value that is attributable to upgrading. The map in Figure 10 has been created by subtracting indicator values in Figure 8 from those in Figure 9, and re-normalizing the result to the range [0,100]. Once again, the results indicate a broad geographic distribution of the largest biodiversity impacts. Significant impact clusters are visible in southern Phôngsali, northwestern Louang Namtha, western Oudômxai, east-central Louangphrabang, northern and southeastern Houaphan, northeastern Xaisômboun, southwest Vientiane, northwest Khammouan, southeast Savannakhét, northeast Champasak and southern Xékong. Clusters of lower but substantial impact are also visible in widely-scattered locations.

8. Summary and Conclusions

In this paper, we have developed, estimated and applied a spatially-explicit model that links road upgrading to forest clearing and potential biodiversity loss in Lao PDR. Our approach combines high-resolution forest-clearing information from Hansen et al. (2013); information on biodiversity and protected areas from IUCN and WWF International; digital road maps from Delorme, Inc.; digital elevation maps from CGIAR; and information on agricultural opportunity values from Deveny et al. (2009). Using the 30 m Hansen data, we estimate cumulative forest clearing rates for all 500 m cells in Lao PDR. For each 500 m cell, we measure the distance to the closest point on the nearest road; the quality of the road link; legal protection status; travel time to the nearest urban market center; the mean agricultural opportunity value of the land; and elevation.

Figure 9: Previous-clearing-adjusted biodiversity indicator after road upgrading

Composite Biodiversity Indicator After Road Upgrading

0.000000 - 12.254070	
12.254071 - 25.399850	
25.399851 - 36.251760	
36.251761 - 45.100590	
45.100591 - 52.995680	
52.995681 - 60.204720	
60.204721 - 67.359550	
67.359551 - 74.795310	
74.795311 - 83.852880	
83.852881 - 100.000000	
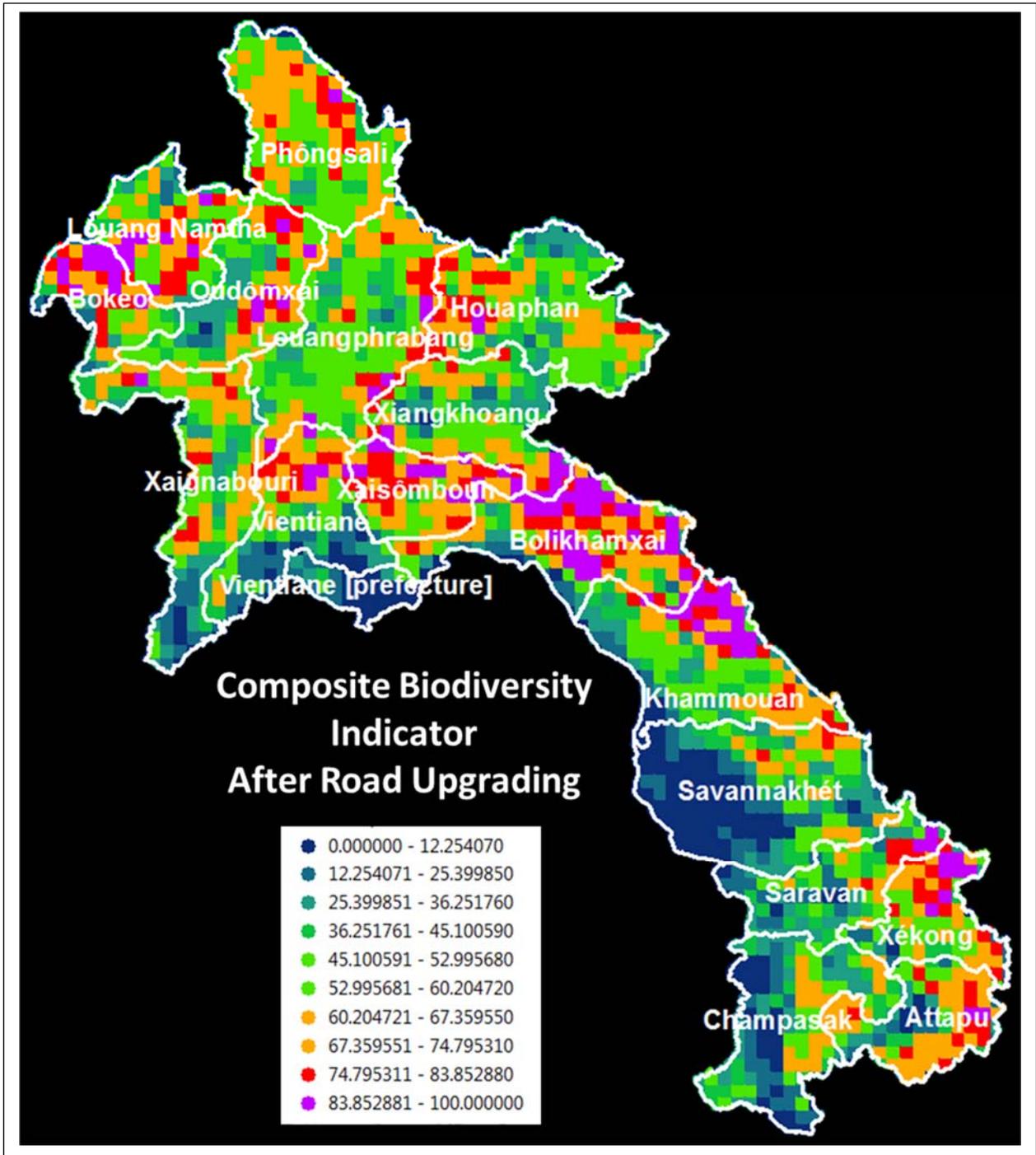
Figure 10: **Change in previous-clearing-adjusted biodiversity indicator after ipgrading (Normalized to [0,100])**

Change in
Biodiversity Indicator
After Road Upgrading

- 0.000000 - 4.696819
- 4.696820 - 11.888430
- 11.888431 - 18.764270
- 18.764271 - 25.408030
- 25.408031 - 32.475510
- 32.475511 - 40.248180
- 40.248181 - 48.800830
- 48.800831 - 58.291850
- 58.291851 - 70.818490
- 70.818491 - 100.000000
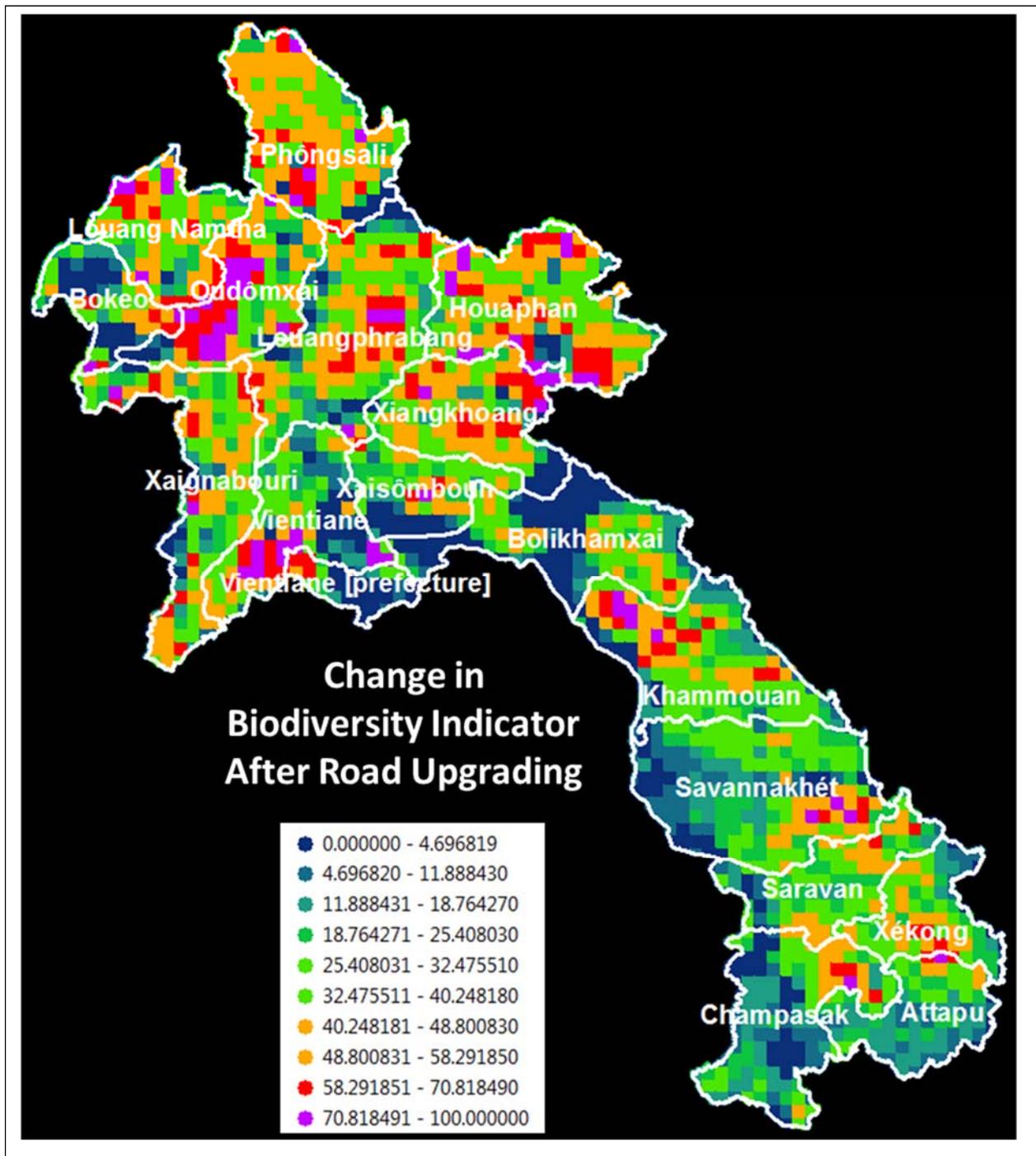
We use an appropriately-specified econometric model to estimate the effects of these variables on the cumulative percent of forest cleared in 2016. Our estimation exercise uses a small random sample to minimize potential spatial autocorrelation problems. The resulting parameter estimates are extremely robust, with the expected signs and very high statistical significance in all cases. Our result for legal protection status is particularly strong, indicating that forest conservation in protected areas has been robust in Lao PDR.

We focus on distance from the nearest road link and its Delorme primary, secondary or tertiary status, which we use as a proxy for road quality. We find an important role for road quality, which reflects the effects of average vehicle speeds and differential maintenance costs in transport to market.[12]

Econometric measurement of road quality effects enables us to estimate the deforestation impact of programs that upgrade secondary and tertiary roads to primary status. To illustrate our methodology, we explore the impact of upgrading all secondary and tertiary roads to primary roads in Lao PDR. We find a highly non-uniform spatial distribution, with several large impact clusters in northern Lao PDR and a few smaller clusters in southern Lao PDR.

With our model-based predictions in hand, we measure biodiversity risk in each 500 m cell using ecoregion information from WWF International and thousands of species range maps from IUCN and Birdlife International. This information is summarized in a new World Bank database that provides georeferenced indicators for ecoregions and species intensity, extinction risk and

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[12] We cannot completely discount simultaneity bias in this estimation exercise, since anticipated returns from future forest clearing might have provided one motivation for past road construction in Lao PDR. However, the relative paucity of forest clearing beyond established urban centers and principal road corridors as recently as 2000 (Figure 2) strongly suggests that other factors were the primary drivers of historical road construction in Lao PDR. Any remaining upward bias from simultaneity will produce some tendency for our methodology to overestimate the potential impact of road improvement on forest clearing. In any case, since "extinctions are forever", we believe that invocation of the precautionary principle in conservation is more than sufficient to accommodate some potential over-estimation.

endemicity for amphibians, mammals, reptiles and birds. We develop 50 measures that incorporate biome status, species density, endemicity, and extinction risk. We normalize each measure to the range [0,100] and develop a composite biodiversity index for each 500 m cell by selecting the maximum normalized value among the 50 measures for that cell. This approach ensures representation for diverse stakeholder concerns, which may range from preservation of critically-endangered amphibians to conservation of small ecoregions that are endemic to Lao PDR.

Available species range maps may not reflect the latest information on forest clearing, which is best represented by the global Hansen data set. Accordingly, we adjust our biodiversity indicator for each 500 m cell by multiplying its biodiversity indicator value by the Hansen estimate of percent forest cover remaining as of 2016.[13] The result is our summary estimate of current biodiversity risk.

To assess the potential impact of road improvement on biodiversity, we compute an expected loss measure for each cell by multiplying its forest-clearing-adjusted biodiversity index by the predicted increase in forest clearing percent from secondary and tertiary road upgrading. We map the results to identify priority areas with high expected losses. We find highly diverse patterns of expected forest clearing and biodiversity loss that would be difficult to anticipate without this kind of analysis.

We believe that these results highlight several important dimensions of ecological risk assessment and road investment policy in Lao PDR. First, newly-available data on forest clearing, species risks and ecoregions provide an unprecedented opportunity to assess ecological impacts at high spatial resolution. Second, assessment can be founded on a rigorous methodology that uses

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[13] As we explain in the paper, this requires combining the Hansen estimate of forest cover in 2000 with the estimate of forest clearing from 2001 to 2016.

Laotian data to derive econometric estimates of responsiveness to road upgrading while controlling for a host of economically-significant forest clearing determinants. Third, a comprehensive biodiversity assessment can incorporate many dimensions of biodiversity risk into a comprehensive index that ensures representation for broad stakeholder concerns.

In this paper, we have developed and illustrated an assessment that incorporates all of these factors. We should also note that our approach is not limited to national-scale assessments. Since our methodology uses high-resolution spatial databases, it can also be "zoomed" for assessment of forest-clearing, ecological risks, and road improvement impacts in specific road corridors or small geographic regions. It can also be extended to other road network databases (e.g. open street maps), and to the analysis of potential impacts for proposed roads that do not currently exist.

In summary, since road upgrading will inevitably accompany rural development programs, we believe that explicit identification of ecologically-vulnerable areas and transport investment impacts can provide at least two valuable types of information. First, with limited budgets, it can help steer road upgrading programs toward corridors where expected biodiversity losses will be minimized. Second, it can inform the adoption of appropriate protection measures in vulnerable road corridors and neighboring areas.

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