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Road Improvement and Deforestation in the Congo Basin Countries

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Abstract

Road construction has often been viewed as the precursor to deforestation, especially in tropical forests. Traditional responses to such threats have been reactive, with attempts to mitigate impacts through physical measures, or the establishment of protected areas. These approaches often have not been entirely successful, especially in areas where economic potential is significant. This paper seeks to mitigate such conflicts by proposing a proactive approach to development planning and environmental policy. It develops a high-resolution spatial model of road improvement impacts that includes ecological risks and the economics of forest clearing. The approach is implemented by estimating the potential impact of road upgrading on forest clearing and biodiversity in eight Congo Basin countries. The paper demonstrates how the detailed analysis can identify areas of high ecological priority as well as areas at high risk of forest loss. The paper contributes to several aspects of the literature. First, it provides the most recent and reliable estimates of the drivers of deforestation in the Congo Basin, with the latest high-resolution satellite data on forest cover changes. Second, it presents novel estimates of biodiversity threats by creating an index that combines and synthesizes several measures of biodiversity loss and impacts. It then develops an empirical framework for estimating the ecological impacts of road improvement. Finally, the paper illustrates how the empirical framework can be used to preempt impacts and avoid potential ecological damage.

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Road Improvement and Deforestation in the Congo Basin Countries

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1. Introduction

Conservation management in tropical forests has traditionally focused on demarcation and protection of relatively large areas that are deemed critical for biodiversity conservation. This strategy seeks to minimize ecological damage by preventing or severely restricting road improvements that increase the profitability of forest clearing within protected areas. In contrast, road improvements often play a central role in agricultural development strategies for poor regions. Potential conflict over the desirability of road improvements is particularly high in forested regions with significant agricultural potential. When protected-area strategies confront this conflict, they may fail to protect critical biodiversity for two reasons. First, governments may seek to minimize economic opportunity costs by siting protected areas in remote regions with low agricultural potential that may not coincide with the areas of highest ecological value. Second, attempts to restrict road improvements in protected areas with strong agricultural potential may fail because economic interests overwhelm the limited resources and political support of conservation managers.

This paper seeks to mitigate such conflicts by developing a high-resolution spatial model of road improvement impacts that includes both ecological risks and the economics of forest clearing. We implement our approach by estimating the potential impact of road upgrading on forest clearing and biodiversity in eight Congo Basin countries: Cameroon, Central African Republic, Equatorial Guinea, Gabon, Republic of Congo, Democratic Republic of the Congo, Rwanda and Burundi.

The remainder of the paper is organized as follows. Section 2 reviews prior empirical research on the economics of forest clearing. In Section 3, we motivate our exercise with a theoretical economic model of road improvement and deforestation. Section 4 describes our

spatially-formatted database, while Section 5 specifies and estimates a deforestation model that incorporates the impact of road improvement. In Section 6, we explore the implications of our results for local, regional and national forest clearing. Section 7 develops an empirical framework for estimating the ecological impacts of road improvement. Section 8 applies our empirical framework to an assessment of local and regional impacts in the Congo Basin countries. Section 9 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). To our knowledge, the present paper is the first extension of such work to Sub-Saharan Africa. Li et al. (2015) have investigated the potential impact of decreased travel time from improvement of road links in the DRC, but their cross-sectional analysis employs land use information (JRC 2003) that predates the new high-resolution satellite data.

3. Modeling the Economics of Road Improvement and Deforestation

As we noted in the introduction, this research aims to develop an analysis of road upgrading and forest clearing that incorporates both economic and conservation concerns. Our objective is a methodology for prospective assessment that can inform infrastructure planning at the outset. To motivate the exercise, we consider the potentially-adverse impact of traditional road improvement planning, in which decision-making is sequential: Decisions on road improvement projects in an area are made first, followed by an EIA (Environmental Impact Assessment) that seeks to mitigate forest clearing by strengthening environmental management rather than affecting the selection of projects. Our modeling exercise shows why coordinated

infrastructure planning in such a sequential decision regime, while otherwise desirable for its direct economic contribution, may actually reduce welfare because it increases deforestation and the associated ecological impacts. It also identifies cases where decentralized decision making generates greater (lesser) deforestation when there are diminishing returns to forest clearance.

Consider two regions, labeled *i* and *j*, which sell their produce at a market at given distances d_i and d_j respectively. Each region is endowed with a given amount of land that can either be left forested, or converted to some alternative use such as agriculture whose outputs are transported to the market and sold at a given price. Let $L_i = L_i^F + L_i^A$ be the total endowment of land in region *i*, where L_i^F is forested land and L_i^A is agricultural land. The payoffs in region *i* to each activity are given by:

1. $\Pi_i = \left(P_i - d_i(1 - q_i)\right)L_i^A - c_i L_i^{A^2} + v(L_i - L_i^A)$

where P_i is the exogenous market price and $0 \leq q_i < 1$ is an index of road quality, with q = 0 representing an unimproved forest track. Improvements in road quality (q) lower transport costs and increase the profitability of agricultural production. With convex costs there are assumed to be diminishing returns to forest conversion ($c_i L_i^{A^2}$). Finally, forests left in their natural state generate a return of *v*, which could include livelihood and other unmarketed benefits obtained from the forest.

Maximizing (1), taking road quality as given, yields the optimal level of clearing (output) in region *i*:

2. $L_i^A = \frac{p_i - d_i(1-q_i)}{2c_i}$,

where $p_i = P_i + v$. The corresponding indirect profit function from the land use decision is:

3. $\Pi_i = \frac{(p_i - d_i(1-q_i))^2}{4c_i} + vL_i$

Region *j* is symmetric and its specification is suppressed for brevity. It is clear from equation (3) that higher market prices or improvements in road quality lead to greater land conversion (i.e. $\frac{\partial L_i^A}{\partial dq_i} = \frac{d_i}{2c_i} > 0$ and $\frac{\partial L_i^A}{\partial dp_i} = \frac{1}{2c_i} > 0$). This straightforward result reflects the fact that higher profitability of agriculture or increased market access renders deforestation and land conversion more profitable. The less well known question is how these incentives might vary under different decision making regimes. In what follows, we compare deforestation levels in each region under two contrasting forms of management. In the first the decision on road quality improvements is made autonomously in each jurisdiction. In the alternative the budget allocation is coordinated to maximize the joint welfare of the two regions. In what follows we assume that environmental impacts are not considered in the decision making process.[1]

Consider first the case of autonomous decision making. For simplicity assume that there is a fixed budget B_i available for road quality improvements in region *i*. The cost of improving road quality is given by: $B_i = rd_iq_i$. If the budget constraint binds then road quality is given by:

4. $q_i^I = \frac{B_i}{rd_i}$

Thus road quality declines with distance (d_i) and the costs of road construction (r). Substituting in (2) the amount of land conversion is:

5. $L_i^A = \frac{p_i - d_i(1 - \frac{B_i}{rd_i})}{2c_i}$

In contrast. under coordinated management the budget is allocated to maximize the joint welfare of the two regions:

[1] This describes a not uncommon situation where decision making is sequential, with decisions on road location made first, followed by an EIA process that typically seeks to mitigate impacts by strengthening environmental management rather than altering road routing.

6. $Max\ W = \frac{(p_i - d_i(1-q_i))^2}{4c_i} + vL_i + \frac{\left(p_j - d_j(1-q_j)\right)^2}{4c_j} + vL_j$

subject to $B_i - rd_i q_i - rd_j q_j$

Which yields solutions for the optimal improvements in road quality:

7. $q_i^c = \frac{c_i B_i + r(c_i\theta_j - c_j\theta_i)}{rd_i(c_{i+}c_j)}$ and $q_j^c = \frac{c_j B_j + r(c_j\theta_i - c_i\theta_{j)}}{rd_j(c_{i+}c_j)}$

where $\theta_k = p_k - d_k$, for ($k = i,j$)

For later use it is instructive to observe that $\frac{\partial q_i}{\partial c_i} = \frac{(c_j B_i + rc_j(\theta_i + \theta_j))}{rd_i[rc_{i+}c_j]^2} > 0$.

As land conversion costs rise in a region, road quality is improved. Intuitively, road investments are made to equate the marginal payoffs from agricultural sales from each region. With diminishing returns to land conversion, it eventually pays to invest in the higher cost region. The following Lemmas compare road investments and deforestation rates under the different regimes:

Lemma 1 If the cost of land conversion between regions differs sufficiently, then road improvements in the high cost region will be greater under coordinated management than under autonomous management (i.e. $q_i^I < q_i^c$ *if* $\frac{c_i}{c_j} > \frac{(B_i + 2r\ \theta_{i)}}{(B_i + 2r\ \theta_{j)}}$*).*

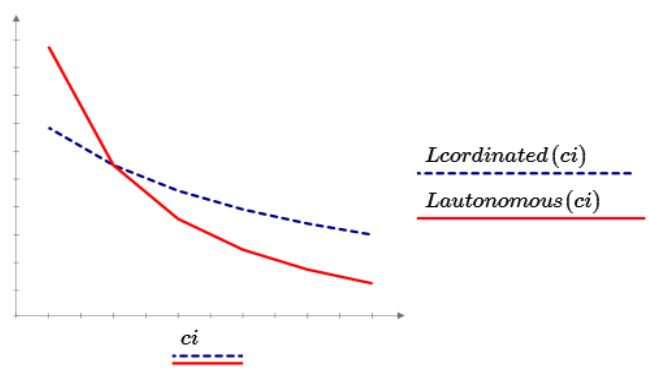
Intuitively, under autonomous management, budgets available to each region are fixed, whereas under coordinated management the region with the higher costs of land conversion could receive a higher allocation to equalize marginal payoffs. An implication of this result is that total deforestation rates may differ across management regimes. This result is summarized in Lemma 2 and illustrated in Figure 1 below.

Lemma 2 Total deforestation rates will differ under the management regimes and will be higher under coordinated management if the cost of land conversion is sufficiently large in one of the regions (*i.e.* $q_i^I + q_j^I < q_i^c + q_j^c$ *if* $c_i > \frac{c_j(B+2r\theta_i)}{(B+2r\theta_j)}$).

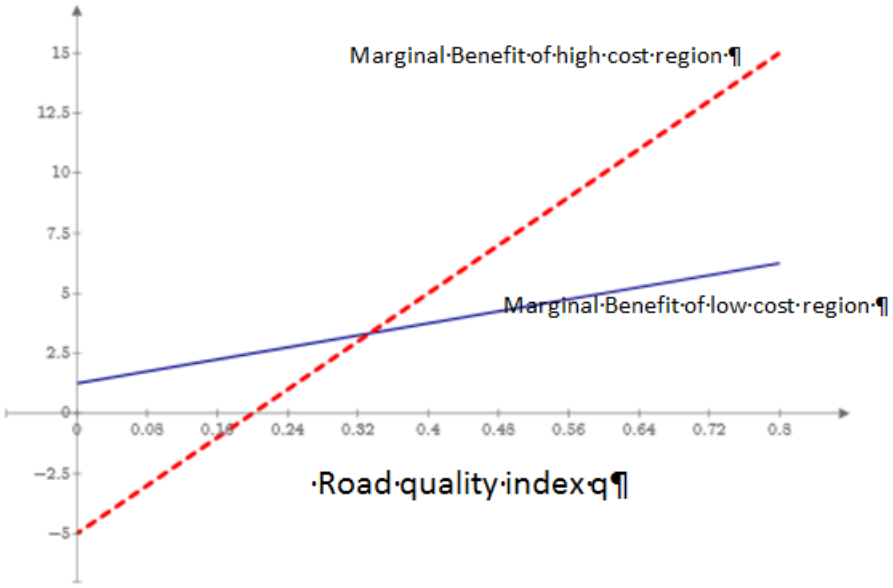
When differences between regions are large, under coordinated management total payoffs are maximized by ensuring that the region with the comparative advantage in land clearing receives greater support on the margin, thus expanding the total volume of land cleared. This result follows from the convex cost of land conversion, which implies that the incremental returns to further deforestation will be lower in the region with a sufficiently high level of land conversion. By implication, coordinated regional infrastructure planning, while promoted for its economic benefits, may actually increase deforestation in a sequential decision regime that selects road projects first and introduces environmental impact analysis ex-post. As an alternative, the approach developed in this paper seeks to improve the decision process by enabling simultaneous consideration of potential road projects and deforestation impacts.

Figure 1: Road planning regimes, road quality and deforestation

Planning regimes and deforestation rates



Marginal net benefits and road quality



4. Data

4.1 Congo Basin Roads

Figure 2 and Table 1 summarize information for seven Congo Basin countries in digital road maps (shapefiles) provided by the Africa Infrastructure Country Diagnostic (AICD) of the African Development Bank Group, augmented by information for the Democratic Republic of the Congo provided by Delorme, and for Equatorial Guinea by DIVA-GIS.[2]

As Table 1 shows, the AICD database includes quality information on 1,710 segments of 380 roads, with data on both road surfaces and road conditions for 941 segments. All seven

[2] Data available online at http://www.diva-gis.org/gdata.

countries are amply represented, with the exception of joint information on surfaces and conditions for roads in Gabon.

Table 1: Congo Basin roads data from the AICD

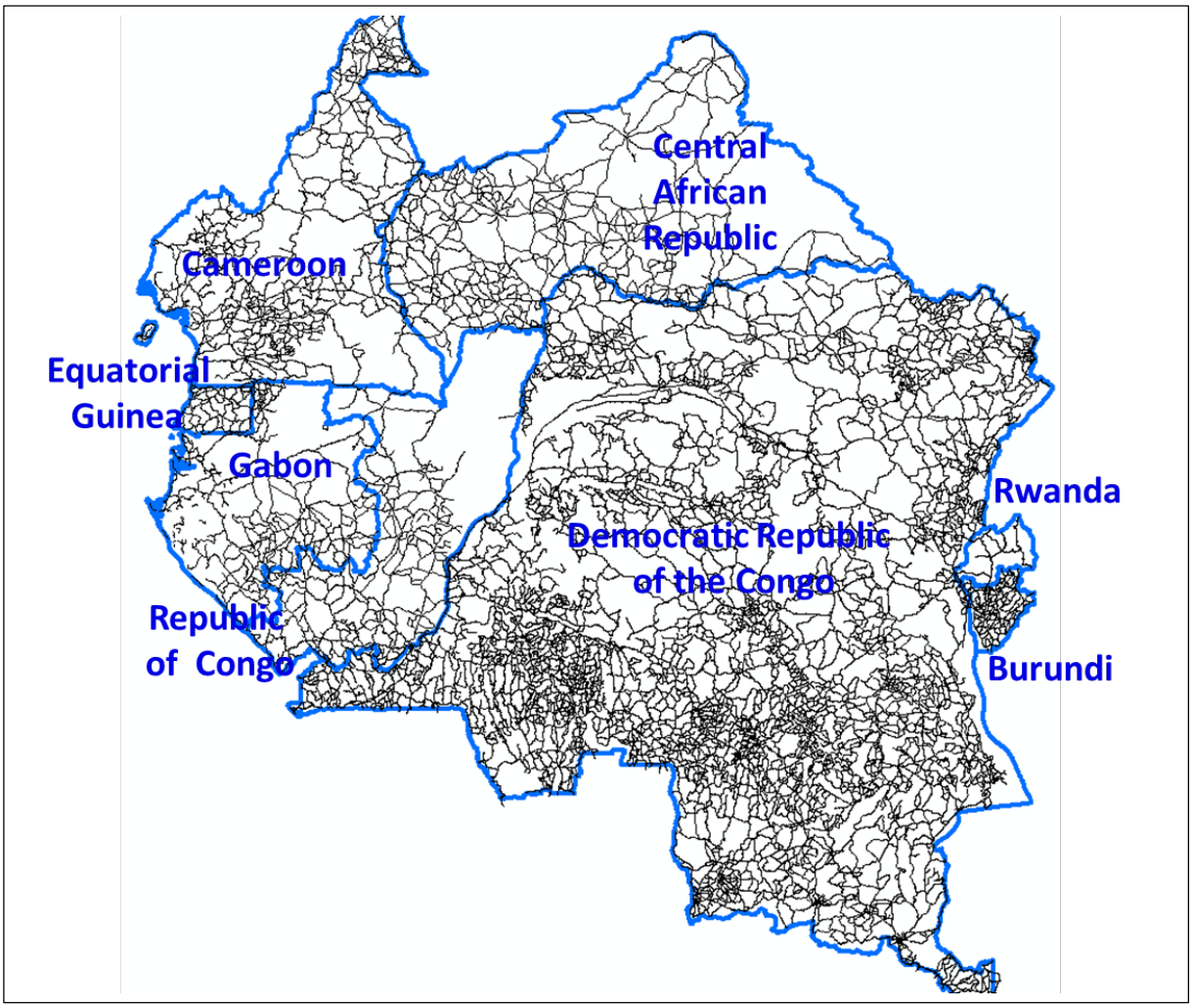
Country	Roads	Road Segments	Segment Data on Road Surface and Condition
Burundi	39	158	37
Cameroon	103	725	397
Central African Republic	30	103	103
Democratic Republic of the Congo	121	347	180
Gabon	51	122	7
Republic of Congo	25	155	144
Rwanda	11	100	73
Total	380	1,710	941

Table 2 summarizes the information on road surfaces and conditions provided by the AICD database. Among rated road segments, 32.6% are asphalt, 26.7% gravel, and 40.7% earth. Asphalt is undoubtedly over-represented in the sample, but this provides useful information for the econometric analysis. Road conditions vary widely across segments, with 30.6% rated good, 25.6% fair, 35.7% poor and 8.1% very poor. Higher quality appears to be over-represented, but again this provides useful information for the econometric analysis.

Table 2: Road surface and condition, AICD database

Road Surface	Good	Fair	Poor	Very Poor	Total	%
Asphalt	102	104	62	39	307	32.6
Gravel	69	41	111	30	251	26.7
Earth	117	96	163	7	383	40.7
Total	288	241	336	76	941	
%	30.6	25.6	35.7	8.1		

Figure 2: Congo Basin roads

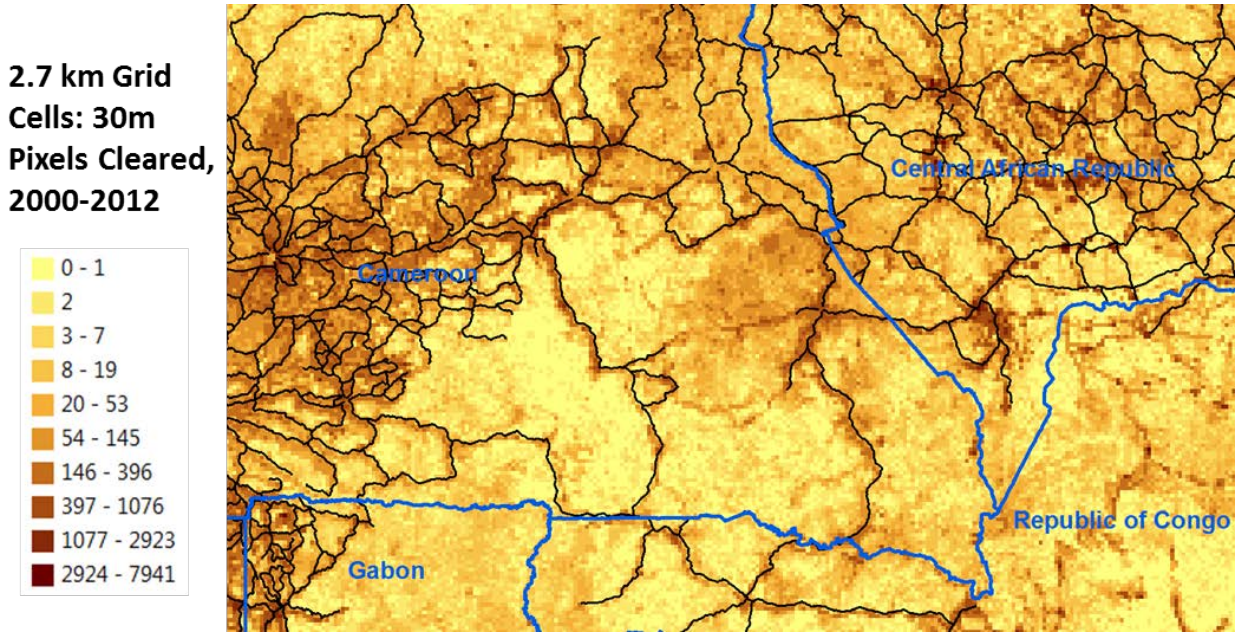


4.2 Forest Clearing

Hansen et al. (2013) have recently published the first high-resolution, consistently-derived estimates of global forest clearing. The data are available as tiff panels at 30 m spatial resolution for 2000-2012. We have converted the tiff panels to annual files in which cleared pixels are assigned the value 1 in the year when most clearing occurred. Uncleared pixels are assigned the value 0. For the exercise in this paper, we have created a tractable database by summarizing the Hansen estimates in 2.7 km grid cells. Each cell contains 8,100 30 m Hansen pixels, so total counts of Hansen cleared pixels within cells are equivalent to deforestation rates.

Figure 3 displays gridded Hansen estimates for the border region of Cameroon, Gabon, Republic of Congo and Central Africa Republic. Each grid cell is color-coded for cumulative percent deforested in 2000-2012. Figure 3 reveals a striking pattern of deforestation along some of the roads in the AICD database. In other cases, however, deforestation is much less pronounced.

Figure 3: Forest clearing and road networks, 2000-2012



To illustrate characteristic patterns of deforestation in road corridors, Figure 4 plots average cleared pixels in grid cells at varying distances from six roads in Cameroon, Central African Republic and Republic of Congo. Although factors other than distance introduce significant variation, each graph displays a pattern of decline from steep to nearly flat over the interval 0 to 15 km, with the steepest portion in the range 0-5 km. The basic shape can be captured by an exponential function that we employ for the econometric analyses in this paper:

$$p = \beta_0 h^{\beta_1}$$

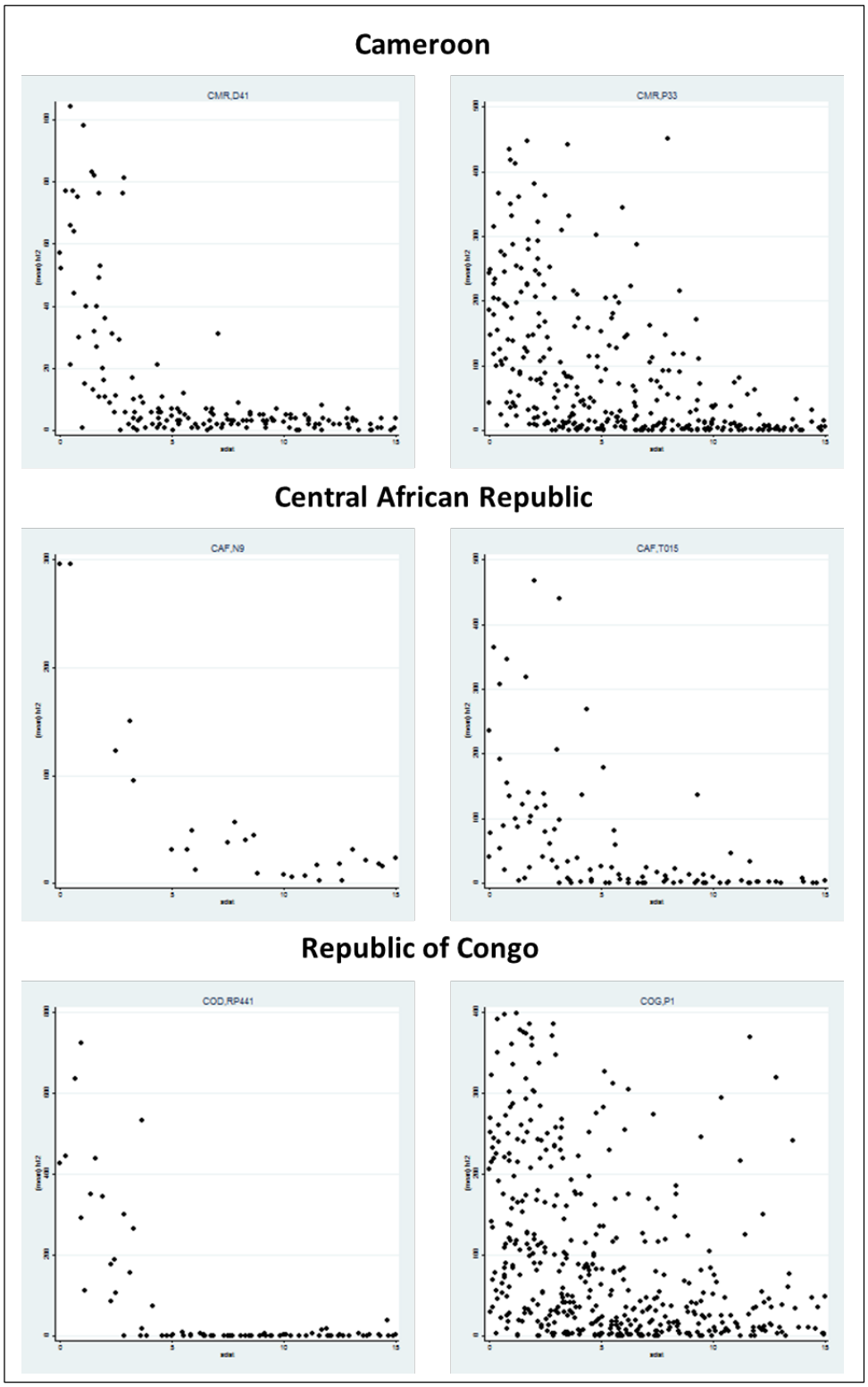
where $\beta_1 < 0$
p = Hansen pixels cleared per grid square
h = Distance from the road

For econometric work, we translate the function to its linear form in the logarithms of h and p.

5. Estimation of the Forest Clearing Model

The estimation exercises in this paper draw on the insights of previous research and the theoretical model in Section 3 to incorporate seven critical determinants of forest clearing in road corridors: road quality, distance from the road, transport cost to the nearest market center, the agricultural opportunity value of the land, terrain elevation, legal protection status and the incidence of violent conflict. Our regressions for the combined sample of Congo Basin countries employ a measure of travel time as a proxy for transport cost. To support a detailed impact analysis, we also estimate separate regressions for the DRC that incorporate an explicit measure of transport cost developed by Ali et al. (2015). We avoid spatial autocorrelation problems by using mean Hansen pixels cleared within grid cells whose distance from a road segment is aggregated to 2.7 km intervals on both sides of the segment.

Figure 4: Average pixels cleared per grid cell vs. distance from road, 2000-2012



We specify the basic estimating equation in log-log form:

$$\log h_{ijt} = \alpha_0 + \alpha_1 \log d_{ij} + \alpha_2 \log p_i d_{ij} + \alpha_3 \log q_i + \alpha_4 \log m_i + \alpha_5 \log c_i + \alpha_6 \log e_i + \alpha_7 \log v_i + \Sigma\beta_t y_t + \varepsilon_{it}$$

where h_{it} = Hansen pixels cleared, grid cell i, road segment j, year t
d_{ij} = Distance of cell i from road segment j
p_i = Legal protection status of cell i
q_i = Condition of road segment j
m_i = Travel time from cell i to the nearest urban center (transport cost for DRC).
c_i = Agricultural opportunity value of cell i
e_i = Elevation of cell i
v_i = Conflict incidence in cell i
y_t = Dummy variable with value 1 in year t and 0 otherwise
ε_{it} = Random error term

5.1 Variable Measures

We stack data sets for individual years in the period 2000-2012, allowing for variable mean clearing in grid cells by year. All variables are calculated as centroid values for 2.7 km Hansen grid cells. Data and sources are as follows.

Hansen pixels cleared: per 2.7 km grid cell, the number of 30 m pixels identified by Hansen, et al. (2013) as cleared, by year, for 2000-2012.

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

Legal protection status: 1 if the parcel 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/.

Condition of the road segment: road surface type and road condition, obtained from the Africa Infrastructure Country Diagnostic (AICD). Surface types are earth, gravel and asphalt. Road conditions are identified as good, fair, poor and very poor. We have translated each variable into ordered cardinal values for estimation: Surface: earth (1), gravel (2), asphalt (3); Condition: very poor (1), poor (2), fair (3), good (4).

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

Transport cost (DRC): total transport cost from each Hansen grid centroid to the nearest urban center with a population of 50,000 or greater, developed from a network analysis.

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

Elevation: Average elevation for a grid cell, calculated from the CGIAR-SRTM data set (3 seconds resolution), aggregated to 30 seconds resolution by DIVA-GIS (http://www.diva-gis.org/gdata).

Conflict incidence: Armed conflict fatalities per unit area, 1997-2007, calculated by Ali, et al. (2015) at 0.017 decimal degrees resolution from data in the Armed Conflict Location Events Dataset (ACLED) (Raleigh, 2010).

5.2 Results

Table 3 presents final estimates for the Congo Basin countries using several estimation techniques. Simultaneity bias may be significant in this context, since forest clearing and road placement are jointly determined in a properly-specified spatial economic model. Our measure of travel time to the nearest urban center along existing roads should therefore be treated as endogenous in our estimating equation. To address estimation bias, we introduce Euclidean distance to the nearest urban center as an instrumental variable. In Table 3, the first two columns present OLS results for travel time and Euclidean distance. Columns (3-5) present three results that employ Euclidean distance as an instrument for travel time: standard 2SLS, GLS (IV) with covariance matrix adjustments for road-specific error variances, and robust regression (IV).

Our results are distilled from numerous experiments that tested the interactions of distance to road with road quality, travel time, agricultural opportunity value, elevation and protection status. The experiments were critical for determining whether these variables affect the slope of the relationship between forest clearing and distance from the road. Only protection status has a strong, consistent effect on the slope, so we have retained the interaction of protection and distance in Table 3. We have included country dummies to control for systematic differences in

forest-clearing intensity. Prior experimentation also revealed that road surface type has no significance for forest clearing, controlling for road condition, so we have excluded this variable from the final regressions.

The estimated coefficients in Table 3 have generally high significance, and their signs are consistent with prior expectations. Among the IV regressions, the GLS corrections for non-uniform error variances across roads result in substantially higher standard errors (and lower t-statistics) but, with the exception of conflict intensity, all variables retain significance levels of 95% or higher. We use the GLS (IV) estimates for our discussion of results.

The most critical variable for this exercise is distance from the road. In Table 3, the results for this variable are strong and consistent across estimators: Ceteris paribus (in GLS (IV)), forest clearing intensity declines 0.67% with each 1% increase in distance. The result for protection status indicates that the relationship between clearing intensity and distance steepens significantly in protected areas.

Our results for road quality are also consistent across specifications, and for numerous experiments that test interactions with distance from the road. Road surface (earth, gravel, asphalt) never has a significant effect,[3] but the impact of road condition (1=very poor; 2=poor; 3=fair; 4=good) is large and highly significant. Neither road surface nor road condition interacts significantly with distance from the road.

Among other regression variables, forest clearing is negatively related to travel time to the nearest market center (elasticity -.63 in GLS (IV)) and elevation (elasticity -.26), and positively related to land opportunity value (.07) and conflict intensity (.03). As expected, our IV results for travel time to the nearest urban center differ markedly from the OLS results.

[3] We have tested the effect of road surface using categorical variables as well as the previously-described cardinal measure.

Table 3: Regression results (all non-dummy variables in log form)

Dependent Variable: Cumulative Hansen pixels cleared

	(1) OLS	(2) OLS	(3) 2SLS	(4) GLS (IV)	(5) Robust (IV)
Distance from road	-0.535	-0.672	-0.672	-0.672	-0.658
	(68.68)**	(102.73)**	(102.73)**	(24.18)**	(102.11)**
Protected area x Distance from road	-0.132	-0.164	-0.164	-0.164	-0.162
	(22.59)**	(28.32)**	(28.32)**	(4.28)**	(28.48)**
Road condition	0.209	0.205	0.205	0.205	0.219
	(14.80)**	(14.48)**	(14.48)**	(2.15)*	(15.71)**
Travel time to nearest urban center	-0.471		-0.628	-0.628	-0.583
	(37.35)**		(30.57)**	(4.84)**	(28.81)**
Euclidian distance to market center		-0.236			
		(30.57)**			
Land opportunity value	0.031	0.069	0.069	0.069	0.067
	(5.95)**	(14.01)**	(14.01)**	(2.04)*	(13.71)**
Elevation	-0.185	-0.258	-0.258	-0.258	-0.244
	(15.79)**	(22.41)**	(22.41)**	(3.23)**	(21.55)**
Conflict intensity (1997 - 2007)	0.025	0.031	0.031	0.031	0.018
	(8.52)**	(10.65)**	(10.65)**	(1.64)	(6.45)**
D2002	0.795	0.794	0.794	0.794	0.791
	(27.88)**	(27.68)**	(27.68)**	(30.68)**	(28.01)**
D2003	1.079	1.078	1.078	1.078	1.077
	(37.91)**	(37.67)**	(37.67)**	(37.51)**	(38.21)**
D2004	1.308	1.306	1.306	1.306	1.307
	(45.98)**	(45.71)**	(45.71)**	(42.66)**	(46.41)**
D2005	1.547	1.546	1.546	1.546	1.543
	(54.48)**	(54.17)**	(54.17)**	(48.81)**	(54.87)**
D2006	1.749	1.748	1.748	1.748	1.748
	(61.69)**	(61.35)**	(61.35)**	(53.31)**	(62.29)**
D2007	1.952	1.951	1.951	1.951	1.952
	(68.91)**	(68.52)**	(68.52)**	(58.06)**	(69.61)**
D2008	2.082	2.081	2.081	2.081	2.079
	(73.54)**	(73.12)**	(73.12)**	(61.97)**	(74.15)**
D2009	2.262	2.261	2.261	2.261	2.257
	(79.94)**	(79.50)**	(79.50)**	(65.67)**	(80.55)**
D2010	2.454	2.453	2.453	2.453	2.444
	(86.78)**	(86.30)**	(86.30)**	(70.15)**	(87.27)**
D2011	2.549	2.548	2.548	2.548	2.539
	(90.16)**	(89.67)**	(89.67)**	(72.52)**	(90.69)**
D2012	2.641	2.640	2.640	2.640	2.630
	(93.45)**	(92.93)**	(92.93)**	(74.81)**	(93.96)**
D[Dem. Rep. of the Congo]	2.043	2.095	2.095	2.095	2.132
	(31.26)**	(31.84)**	(31.84)**	(6.67)**	(32.89)**
D[Cameroon]	0.336	0.322	0.322	0.322	0.279
	(5.05)**	(4.81)**	(4.81)**	(0.98)	(4.24)**
D[Gabon]	0.594	0.304	0.304	0.304	0.415
	(5.35)**	(2.73)**	(2.73)**	(0.60)	(3.79)**
D[Republic of Congo]	0.547	0.387	0.387	0.387	0.411
	(8.01)**	(5.67)**	(5.67)**	(1.16)	(6.11)**
D[Central African Republic]	0.164	0.114	0.114	0.114	0.062
	(2.43)*	(1.70)	(1.70)	(0.35)	(0.92)
D[Rwanda]	0.791	0.805	0.805	0.805	0.805
	(9.38)**	(9.50)**	(9.50)**	(2.21)*	(9.63)**
Constant	5.339	4.252	6.985	6.985	6.668
	(46.48)**	(39.65)**	(45.28)**	(7.06)**	(43.88)**
Observations	44743	44743	44743	44743	44743
R-squared	0.56	0.56	0.56	0.56	0.56

Absolute value of t statistics in parentheses
*** significant at 5%; ** significant at 1%**

The yearly dummy variables increase steadily in size, reflecting the increase in cumulative clearing, but the increments decrease markedly during the period 2000-2012. All country dummies except CAR's are highly significant (and highly-varied) in the 2SLS and robust (IV) results, although the GLS (IV) results suggest that the large positive estimate for the DRC is the most robust in the set.[4]

6. Implications for Forest Clearing

We explore the implications of our results with the GLS (IV) estimates in Table 3 and the Appendix table for DRC, employing a three-step approach: (1) We use the regression variables to predict forest clearing ($\widehat{f_0}$) for 520,732 2.7 km pixels in the eight Congo Basin countries. Where road condition estimates are missing (most often for rural tertiary roads), we assume very poor conditions (value 1). (2) We simulate the effect of upgrading by progressively resetting all road conditions to higher values (2,3,4) and re-predicting forest clearing ($\widehat{f_1}$) for all pixels. (3) To ensure consistency with the initial pattern of deforestation, we form the ratio [$\rho = (\widehat{f_1})/(\widehat{f_0})$] and multiply by actual clearing (f) to obtain the final prediction result [$\hat{f} = \rho f$].

6.1 Micro-Results: Kasese, DRC

Using the GLS (IV) results in Table 3, we illustrate our approach and the micro-implications with a road segment in the Kasese area of Maniema Province, DRC (Figure 5). We simulate upgrading with two adjustments to the data. Starting with the initial condition (1 - very poor), we improve the condition in unit increments (2, 3, 4). At the same time, we adjust the data on travel time to the nearest urban center to reflect the improvements. For this adjustment,

[4] As previously noted, we have also tested the model separately for the DRC. We include the DRC results in Appendix 1 and explore their implications in Section 6.2. In comparison with Table 3, we obtain identical signs and simlar significance levels for distance from the road, its interaction with protected-area status, road condition, Euclidian distance from the nearest urban center, and elevation. The DRC parameter estimates for road condition are higher than the Congo Basin estimates in Table 3. Some variation in estimated parameter values is unsurprising, given the huge difference in degrees of freedom (44,743 observations for the Congo Basin vs. 13,422 for the DRC).

we estimate average road speed by road condition from estimates for 12,322 road segments in the DRC produced by Ali, et al. (2015).

Figure 5: Kasese, Maniema Province, DRC

Table 4 presents our results, along with derived travel time multipliers for a road segment whose initial condition is very poor. In this condition, average travel speed on the segment is 24 km/hr. Progressive improvements in the segment's condition increase average speed to 36, 55 and 73 km/hr, respectively. With increased speed, travel time to the nearest urban center falls to 75%, 49% and 33% of the initial time.[5]

Table 4: Road condition and travel time to nearest urban center

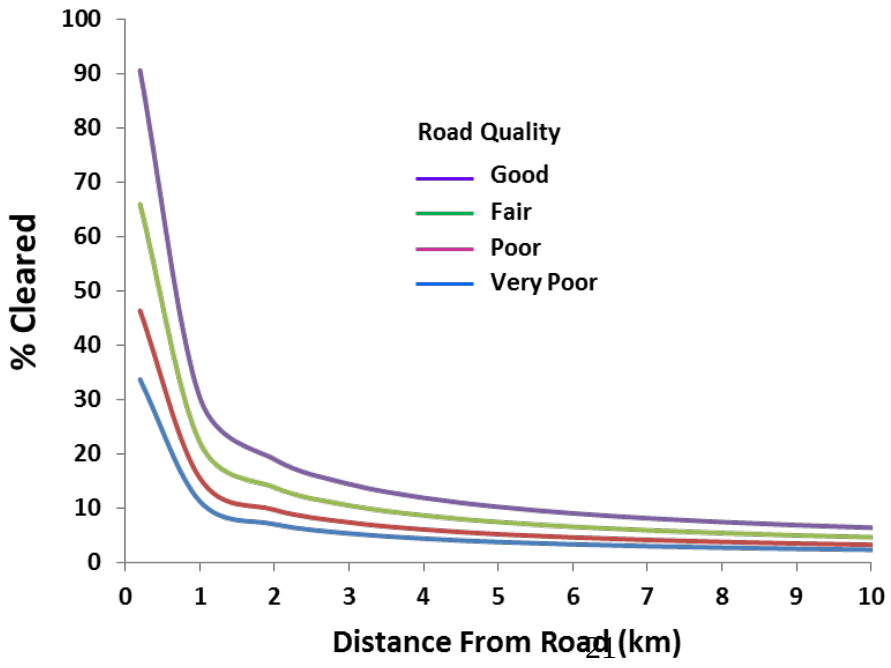
Road Condition	Average Speed (km/hr)	Travel Time Multiplier
1	24	1.00
2	36	0.75
3	55	0.49
4	73	0.33

[5] A reduction in travel time should also produce an increase in the opportunity value of land in the road corridor. The opportunity value measure employed for this exercise is based on physical measures (e.g., soil quality) and does not incorporate the effect of distance to market. We are therefore unable to estimate the effect of road quality improvement on this variable. By implication, our results should be interpreted as conservative estimates of road improvement impacts on forest clearing.

Figure 6 presents our forest clearing results for the Kasese road segment as its condition improves from very poor (1) to good (4). With the road in very poor condition (value 1), 34% of previously-forested land is cleared within 200 meters of the road. Further away, clearing declines to 11% at 1 km, 7% at 2 km and 2% at 10 km. When the segment's condition is improved to fair (value 3), predicted clearing percent at 200 m, 1 km, 2 km and 10 km is 66%, 22%, 14% and 5%, respectively. With further upgrading to good condition (value 4), clearing at the four distances increases to 91%, 30%, 19% and 6%, respectively.

Two patterns are noteworthy in these results. First, upgrading from very poor to good produces near-complete deforestation within a narrow corridor straddling the road. Second, deforestation intensity falls rapidly as distance from the road increases. Despite this decline, the overall spatial magnitude of road improvement's impact is striking. To illustrate, suppose that we adopt 5% clearing as the criterion for identifying pixels at the outer margin of corridor deforestation. For the road in poor condition, this yields an affected corridor 6 km wide (3 km on either side of the road). Upgrading to good condition widens the affected corridor to 26 km.

Figure 6: Effect of road quality on forest clearing intensity



6.2 Regional Results -- Eastern DRC

We explore the regional implications for eastern DRC, using the DRC-specific regression results reported in the Appendix because they incorporate a more precise measure of transport cost developed by Ali, et al. (2015).[6] Figures 7, 8 and 9 illustrate the predicted impact of road upgrading for adjoining parts of Kasai Oriental, Equateur, Orientale and Kivu Provinces of eastern DRC. Figure 7 displays cumulative forest clearing from 2000 to 2012 in our Hansen 2.7 km pixels. Colors range from dark green for clearing below 5.3% to dark brown for clearing between 59.2% and 99.9%. Intensive clearing is almost entirely within relatively narrow corridors along roads between urban areas, with clusters of clearing in settled areas where road networks are relatively dense. Clearing is generally moderate: typically 5-16% in rural areas, 5-33% in areas with denser road networks, and, in rare cases, higher than 33% near major settlements.

For an instructive contrast, Figure 8 uses the same color coding to display the predicted result of generalized road upgrading to good condition (value 4). Changes are particularly striking in Kasai Oriental and Kivu: Clearing near many rural roads moves into the range 33%-59% and large areas near dense road networks move into the range 59% -99.9%. The differences between Figures 7 and 8 are displayed in Figure 9, which provides a striking picture of the widespread "browning" that accompanies generalized road upgrading.

6.3 National Results -- DRC

[6] From Ali, et al. (2015), we incorporate the impact of road upgrading on transport cost using an approach analogous to the method illustrated in Table 4. We calculate unit transport cost (transport cost to the nearest market center divided by distance) for road condition 4 (good). For each pixel, we multiply this value by distance to the nearest market center to estimate transport cost after upgrading.

Figure 10 extends the regional results to the national level for DRC, color-coding by predicted change in the deforestation rate along road corridors 2 km wide. Our results are presented at the sub-district level. For each sub-district, we compute mean deforestation rates

Figure 7: Eastern DRC: Percent clearing along roads before upgrading

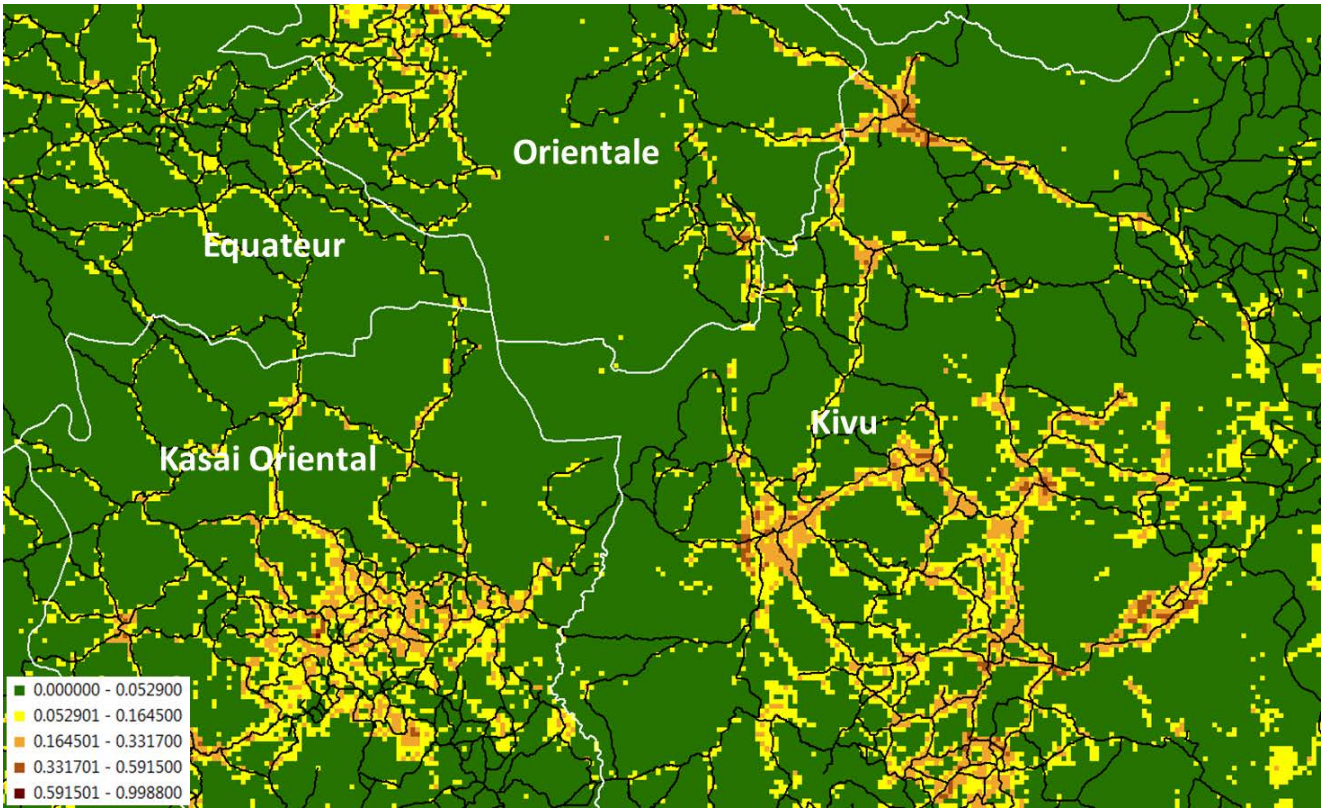


Figure 8: Eastern DRC: Percent clearing along roads after upgrading

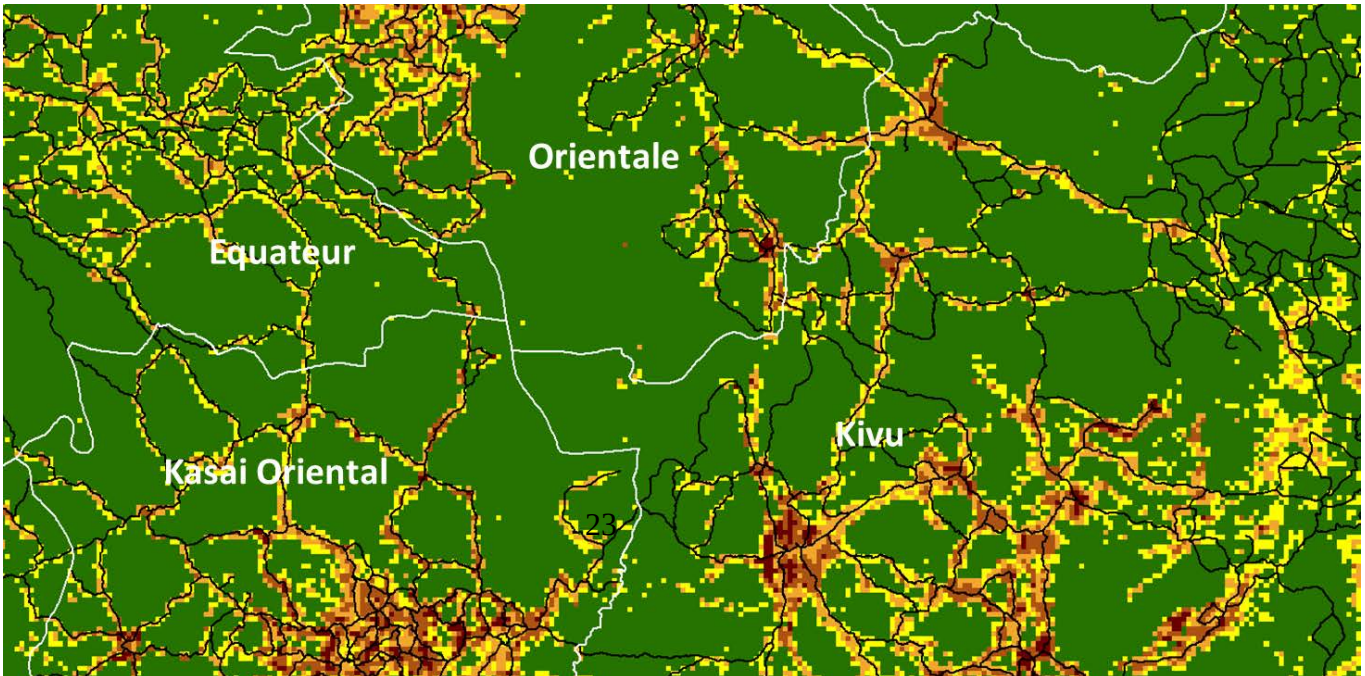
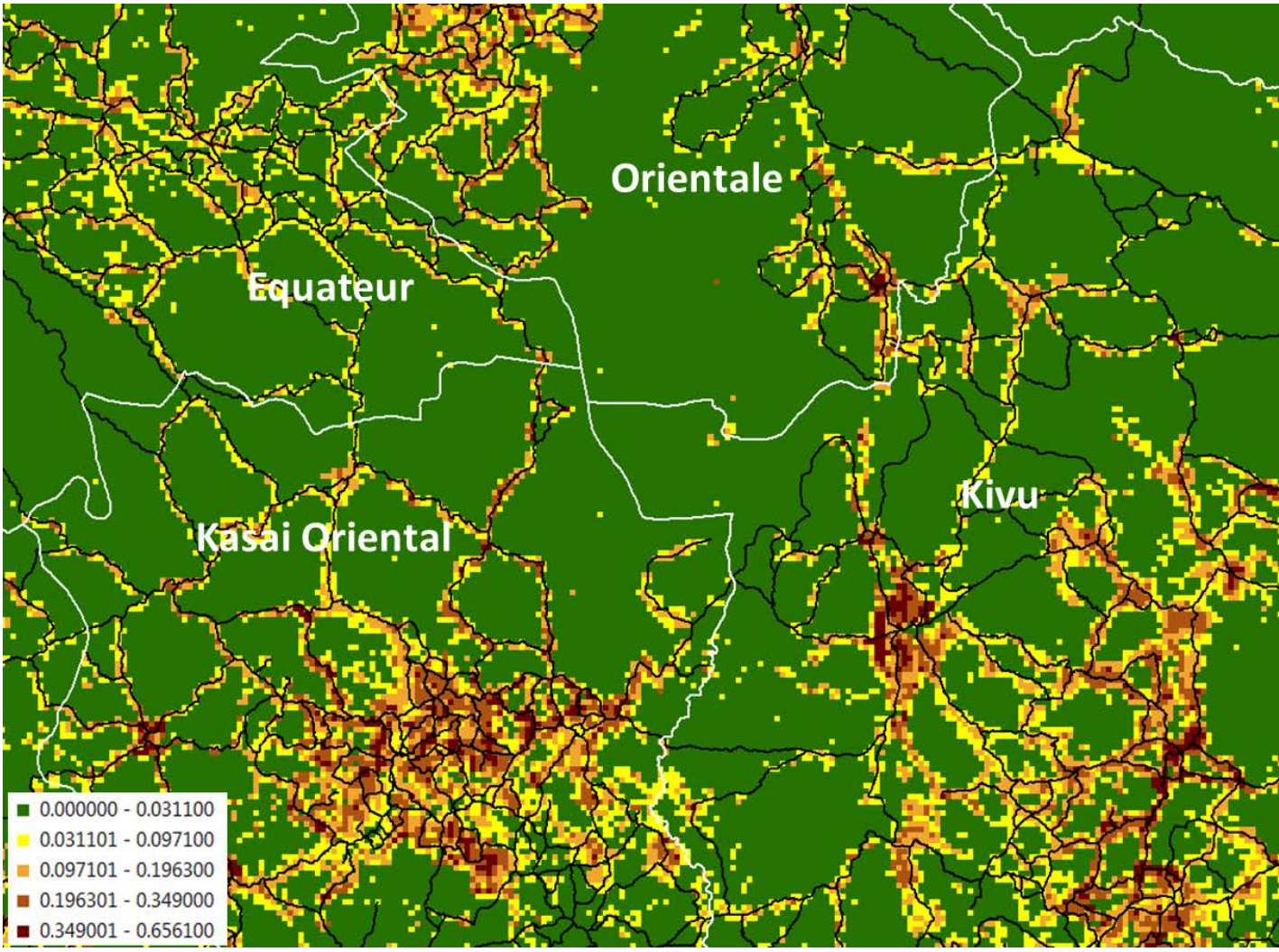


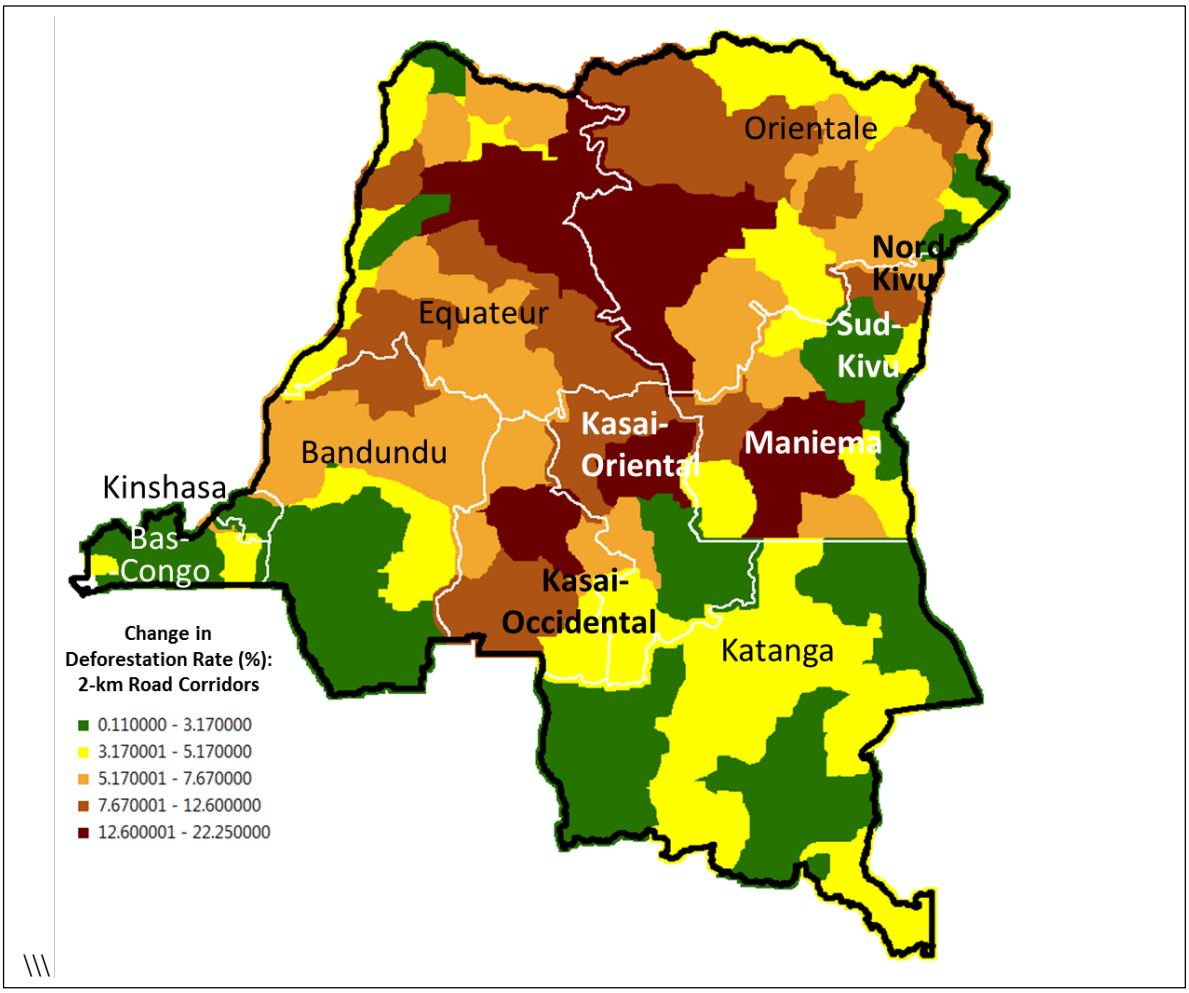
Figure 9: Eastern DRC: Change in percent clearing along roads with upgrading



before and after upgrading, for pixels whose centroids lie within 2 km corridors straddling all roads in the sub-district.

Figure 10 displays changes in mean deforestation rates produced by road upgrading to level 4 (good). The heaviest impacts (increases of 12.6% to 22.3%) are evident in west Orientale, east Equateur, central Kasai-Occidental, northeast Kasai-Oriental and central Maniema. Adjacent areas in all five provinces also have significant impacts (7.7% to 12.6%). The heaviest impacts are concentrated in relatively isolated rain forest areas with poor roads, since market access for these areas would be most improved by upgrading. Overall, our results indicate that 10-20% increases in deforestation would be common after upgrading in rain forest road corridors.

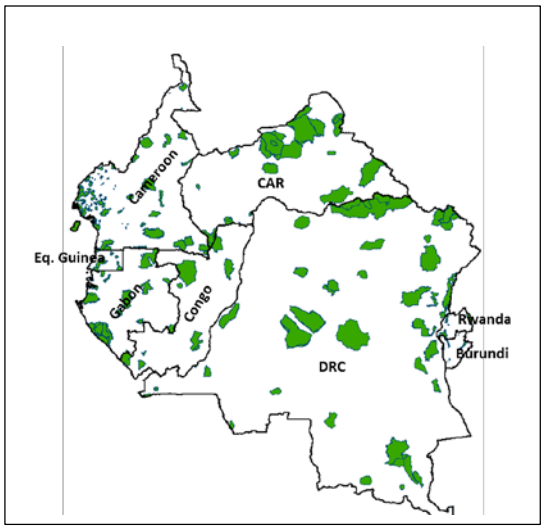
Figure 10: Changes in road corridor deforestation with generalized upgrading



7. Incorporating Biodiversity

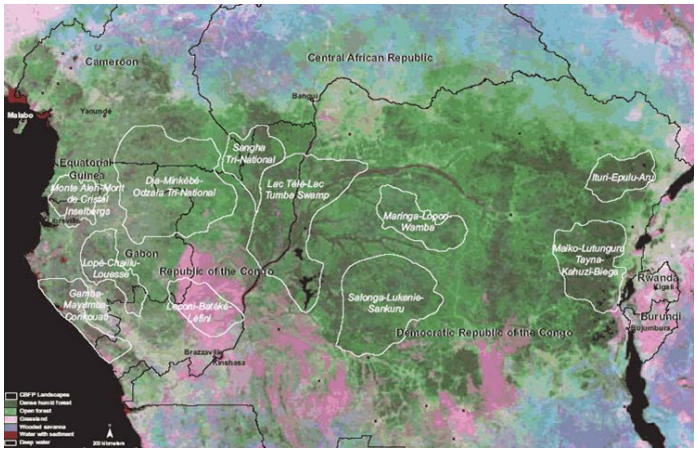
Deforestation may reduce or eliminate critical habitat for endangered animal and plant species. Effective protection of biodiversity requires a variety of approaches that are tailored for different political, economic and geographic conditions. In the Congo Basin countries, three broad approaches have emerged: (1) Traditional strategies that focus on monitoring, enforcement and local community outreach for the protected areas identified in Figure 11.

Figure 11: Protected areas in the Congo Basin countries



(2) Strategies that identify ecologically-representative areas where scarce administrative and financial resources can be focused on the conservation components of integrated development plans. To illustrate, Figure 12 displays eleven "Priority Landscapes" in the Congo Basin countries that have been identified by a consortium of national and international conservation planners (WWF, 2000).

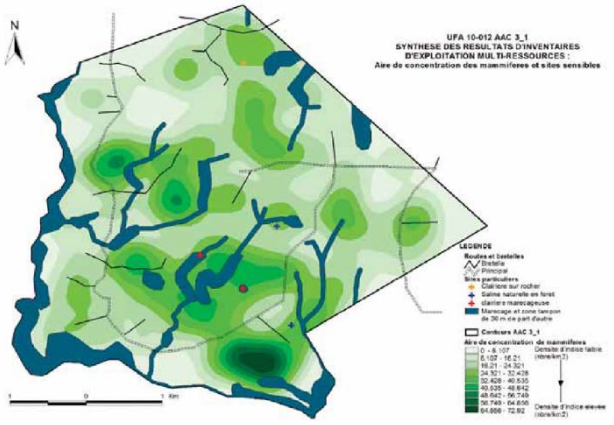
Figure 12: Priority landscapes in the Congo Basin countries



Source: WWF (2000)

(3) "Ecological gradient" strategies that use high-resolution biodiversity measures to steer infrastructure development toward sites where ecological damage will be minimized. An illustrative planning problem is displayed in Figure 13, which overlays roads and an ecological gradient that measures mammal concentrations in the Cameroon portion of the Sangha Tri-National Priority Landscape.

Figure 13: Sangha Tri-National Priority Landscape, Cameroon



Source: IUCN (2010), Figure 3, p. 90

As Figure 13 shows, some road corridors are in areas of modest mammal concentration, while others pass through areas of high concentration. With such information, an ecological gradient strategy attempts to minimize ecological damage by favoring road improvements in areas of modest concentration. We adopt the ecological gradient approach for this paper, because it incorporates both economic and ecological concerns into infrastructure planning.

More generally, ecological gradient strategies require high-resolution data on concentrations of diverse species and their vulnerability to encroachment and habitat loss. This paper mobilizes such information to develop ecological gradients (henceforth ecogradients) for the Congo Basin countries. We develop ecogradients for animal species using digital range maps (shapefiles) provided by the International Union for the Conservation of Nature (IUCN) and BirdLife International. Table 5 summarizes the results of range map overlays for the Congo Basin and global tropical forests. Among species classes, the Congo Basin is most heavily represented among birds (1,141/8,370 (13.6%)) and mammals (484/3,547 (13.6%)), followed by amphibians (264/4,467 (5.9%)) and reptiles (37/1,744 (2.1%)). Overall, the Basin accounts for 10.6% of global tropical forest species.

Table 5: Animal species counts for tropical forest areas

	Congo Basin Tropical Forest Areas[a]	Global Tropical Forest Areas[a]	Congo Basin Percent of Total
Amphibians[b]	264	4,467	5.9
Birds[c]	1,141	8,370	13.6
Mammals[b]	484	3,547	13.6
Reptiles[b]	37	1,744	2.1
Total	1,926	18,128	10.6

[a] Based on a Vegetation Continuous Field (VCF) threshold value of 25 in 2000. See Hansen, et al. (2003).
[b] Shapefiles provided by IUCN at http://www.iucnredlist.org.
[c] Shapefiles provided by BirdLife International on request.

7.1 Ecological Gradients for Animal Species

7.1.1 Species Density

A useful ecogradient database should have tractable size, while incorporating sufficient spatial resolution for realistic local applications. This exercise employs a 5 km spatial grid that covers the Congo Basin with 133,782 square cells. We measure species density by overlaying the grid on 1,926 range maps for Basin species and registering the presence or absence of each species in each grid cell.

7.1.2 Species Vulnerability

Species density provides critical information for developing ecogradients, 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 grid cell. Species that reside in very few grid cells may be particularly vulnerable to habitat encroachment. Endemicity can be computed from the database constructed for this paper.

(2) A measure of *extinction risk* that adds the insights of the international scientific community. Recent work by Mooers, et al. (2008) has explicitly modeled the relationship between extinction probability and the risk indicator that is provided for each species in the IUCN and BirdLife databases.[7]

Endemicity

Our ecogradient database includes endemicity -- the percentage of each species' range that is found in each grid cell. Endemicity treats all species equally at the global level, since each species has a total count of 1. Total endemicity for each grid cell -- the sum of its species

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

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.

Extinction Risk

Species differ in vulnerability for many reasons that are not captured by our endemicity measure. To incorporate these factors, we use the threat status code assigned to each species by the IUCN's Red List. An appropriate measure of vulnerability in this context is extinction risk, so we convert Red List status codes to extinction probabilities using the methodology of Mooers, et al. (2008). 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 6 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 recent work by Isaac, et al. (2007), who combine a direct extinction risk measure with a measure of each species' isolation on a phylogenetic tree.[8]

[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 6: Normalized species aggregation weights[a]

		Normalized Extinction Probabilities			
			IUCN: Future Years		
IUCN Code	Status	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).

Table 6 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 7. 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 7: Implications of alternative weighting schemes

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

7.1.3 Composite Ecogradients for Animal Species

With such potentially-huge differences in metrics, it is important for an ecogradient methodology to accommodate different risk-weighting schemes in a consistent and plausible way. In addition, it seems highly unlikely that the weights assigned to species classes (amphibians, birds, mammals, reptiles) by the conservation community would be proportional to their grossly unequal representation in overall species counts (Table 5). Finally, conservation specialists are not likely to agree on the relative importance that should be assigned to endemicity and extinction risk in composite ecogradients.

To accommodate these diverse concerns, we adopt a conservative strategy for ecogradient construction. First, we divide all measures of endemicity and extinction risk by their maximum values and multiply by 100 to create indexes in the range 0-100. This ensures comparability in measurement. Then, for each grid cell, we select the maximum index value as our ecogradient measure for the cell. This approach ensures parity treatment for all animal species and alternative vulnerability indicators in determining composite ecogradients.

7.2 Incorporating Biomes

An ecogradient measure based on animal species alone provides 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 14). 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 ecoregions in the Congo Basin countries (Figure 15). Then we extend geographic coverage to surrounding countries that include parts of those ecoregions. Figure 16 identifies these countries, which extend from Senegal to South Sudan in the north, and from Angola to Malawi in the south. For the group of selected countries, we compute the percent of total area 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 pixel in the Congo Basin countries. This accounting assigns high values to pixels in smaller ecoregions, where clearing single pixels may pose more significant threats to biome integrity.

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

Figure 14: WWF Terrestrial Ecoregions

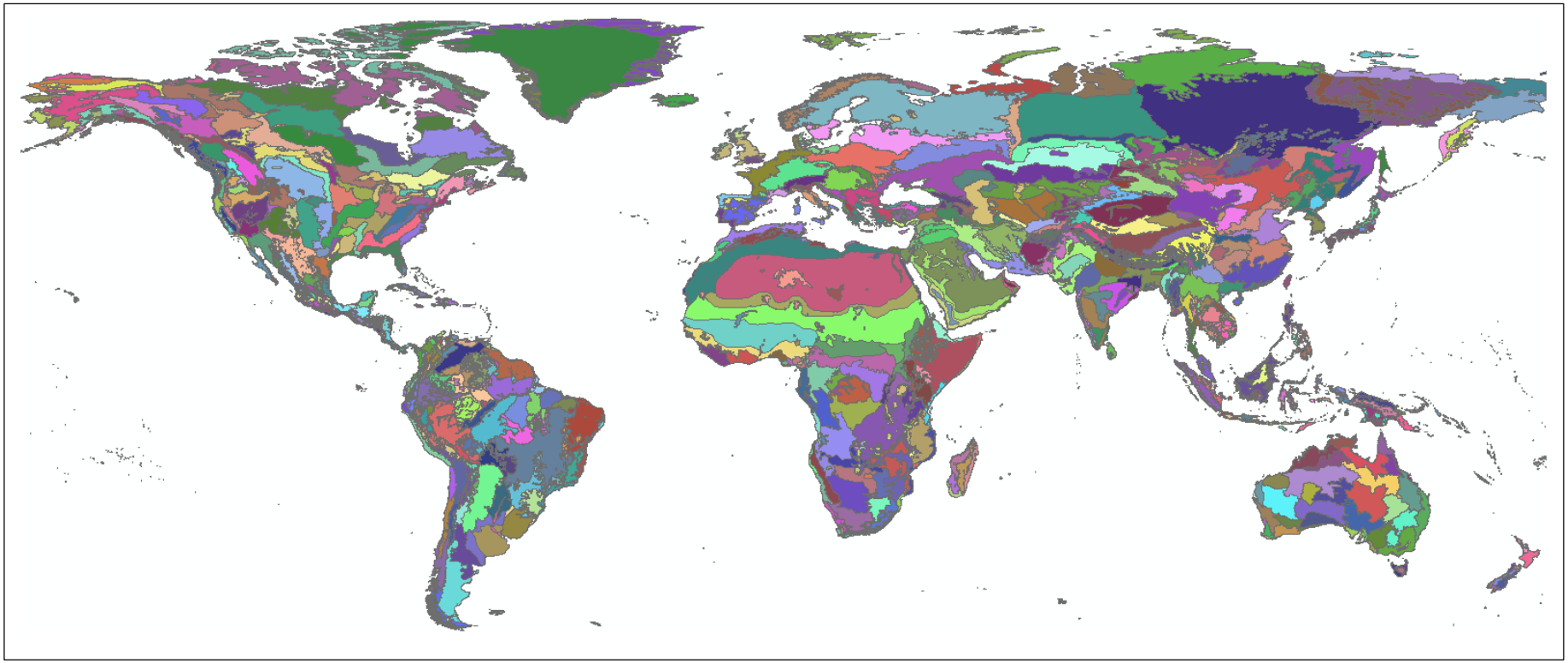


Figure 15: WWF Terrestrial Ecoregions in the Congo Basin countries

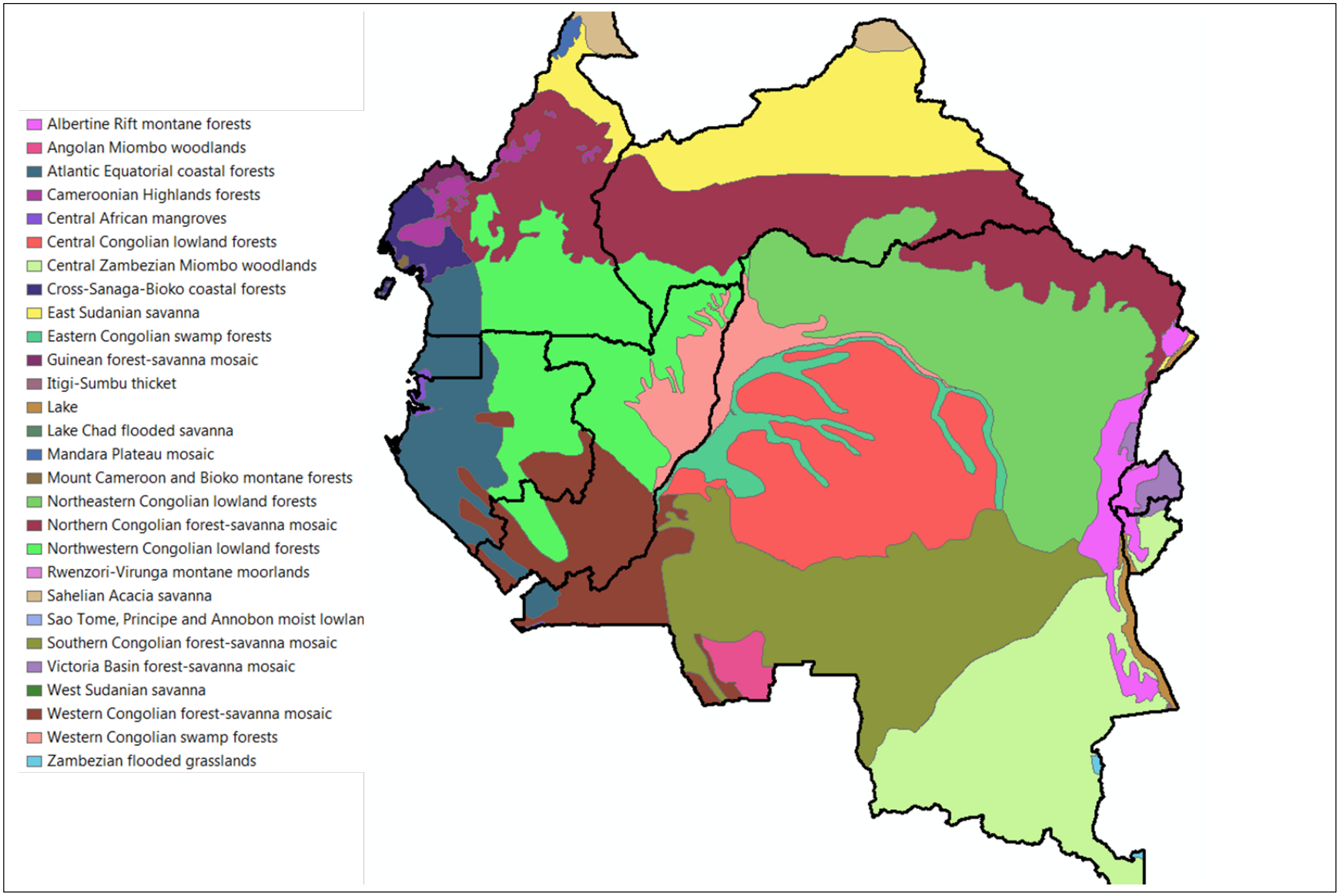
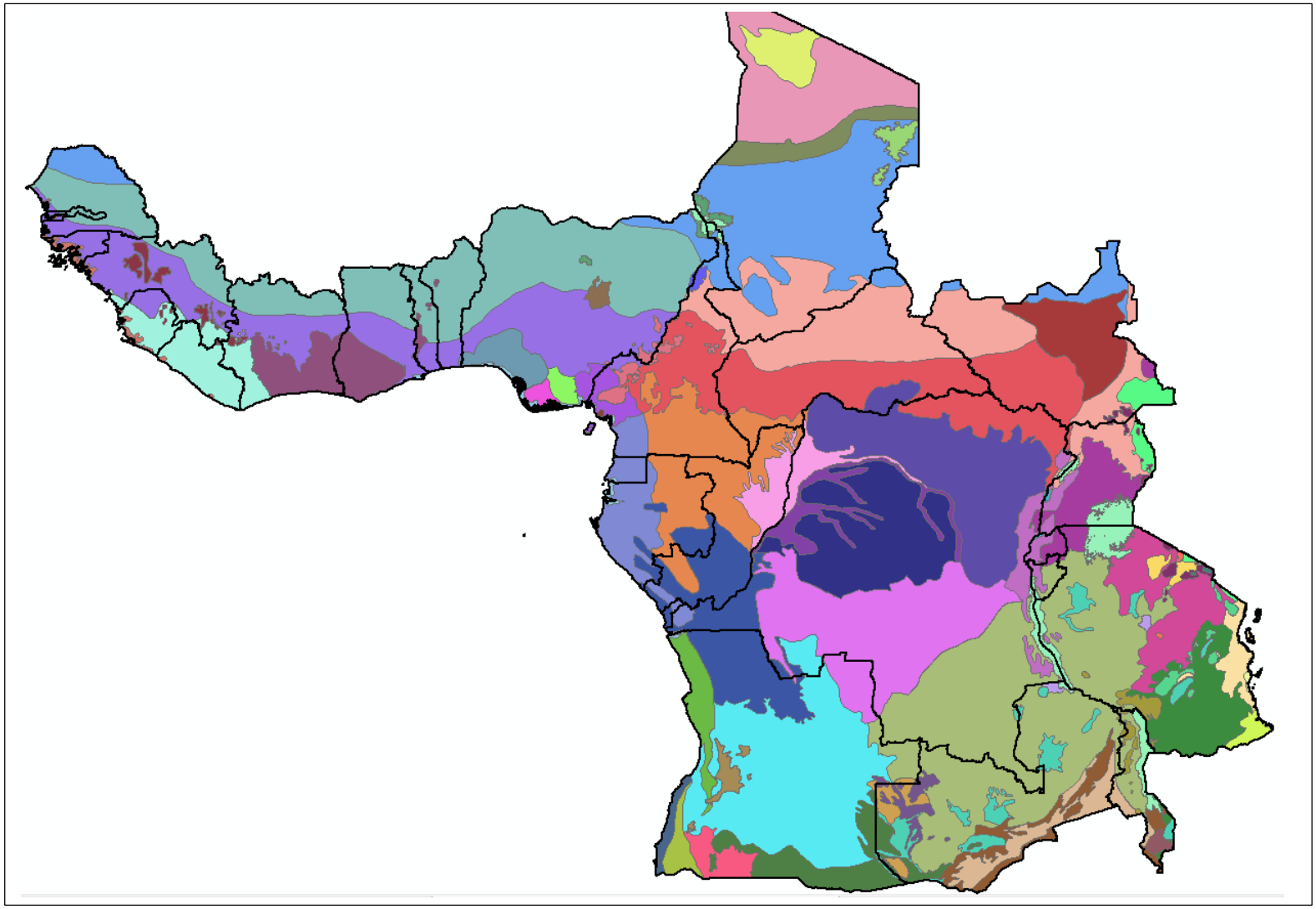


Figure 16: WWF Ecoregions in the Greater Congo Basin region



7.3 A Composite Biodiversity Indicator

No consensus exists on relative weights for our animal species and ecoregion indices in a composite index. As before, we could provide a conservative accommodation by normalizing both indices to range 0-100 for each pixel and choosing the larger index value as our measure. However, the ecoregion index is far more skewed than the species index. As a consequence, choosing maximum values for each normalized index pair will select the species index in the great majority of cases. For a more robust and balanced measure, we substitute ranks -- measured as percentiles -- and choose the greater percentile value for each pixel.

Figures 17, 18 and 19 map the two component indexes and the composite index as percentiles. We have included national and provincial boundaries for ease of reference. Comparison provides a clear rationale for the composite index, since the two component maps look very different. The species map (Figure 17) reflects counts, extinction threats and endemicity measures for 1,976 species in the Congo Basin countries. The 90-percentile areas are mostly in southern and western Cameroon, eastern DRC, Rwanda and Burundi. Intermediate 70- and 80-percentile areas separate these from the lower-percentile areas.

The ecoregion map (Figure 18) has some overlaps with the species map, particularly for 90-percentile areas in western Cameroon, eastern DRC, Rwanda and western Burundi. The two maps also overlap in northern and southern low-percentile areas. However, they have completely different patterns in the central area, which is very low-percentile in the species map but relatively high-percentile in the ecoregion map.

Figure 19 combines both sets of information, displaying the highest percentile value for each pixel. [10] This approach ensures some “leveling up”, visible in the near-absence of values in

[10] All indices are measured as centroid values for our 2.7 km Hansen pixels. Where necessary, we have resampled with the Stata routine geonear for pixel-level matching.

Figure 17: Animal species index, Congo Basin countries

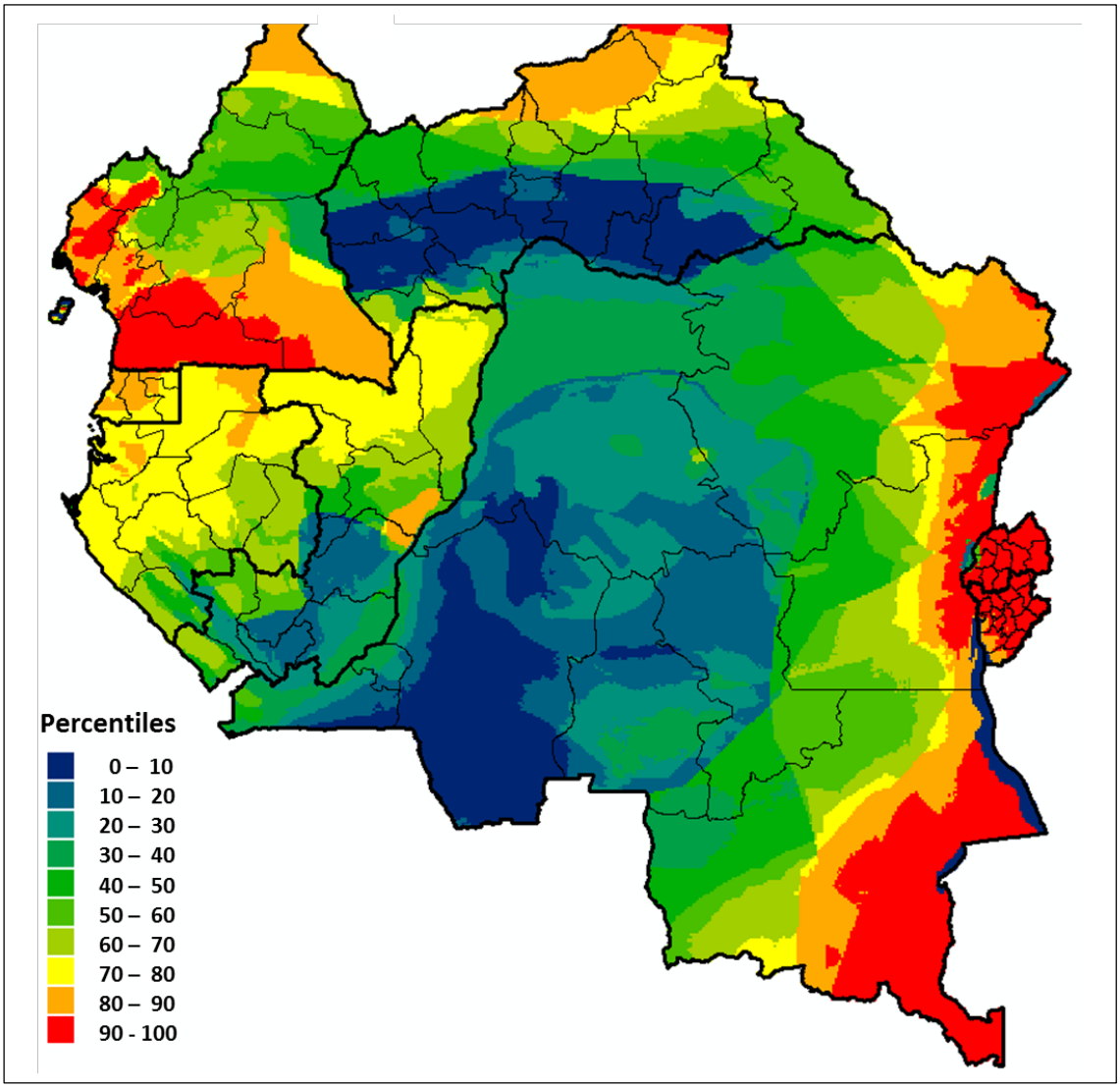


Figure 18: Ecoregion index, Congo Basin countries

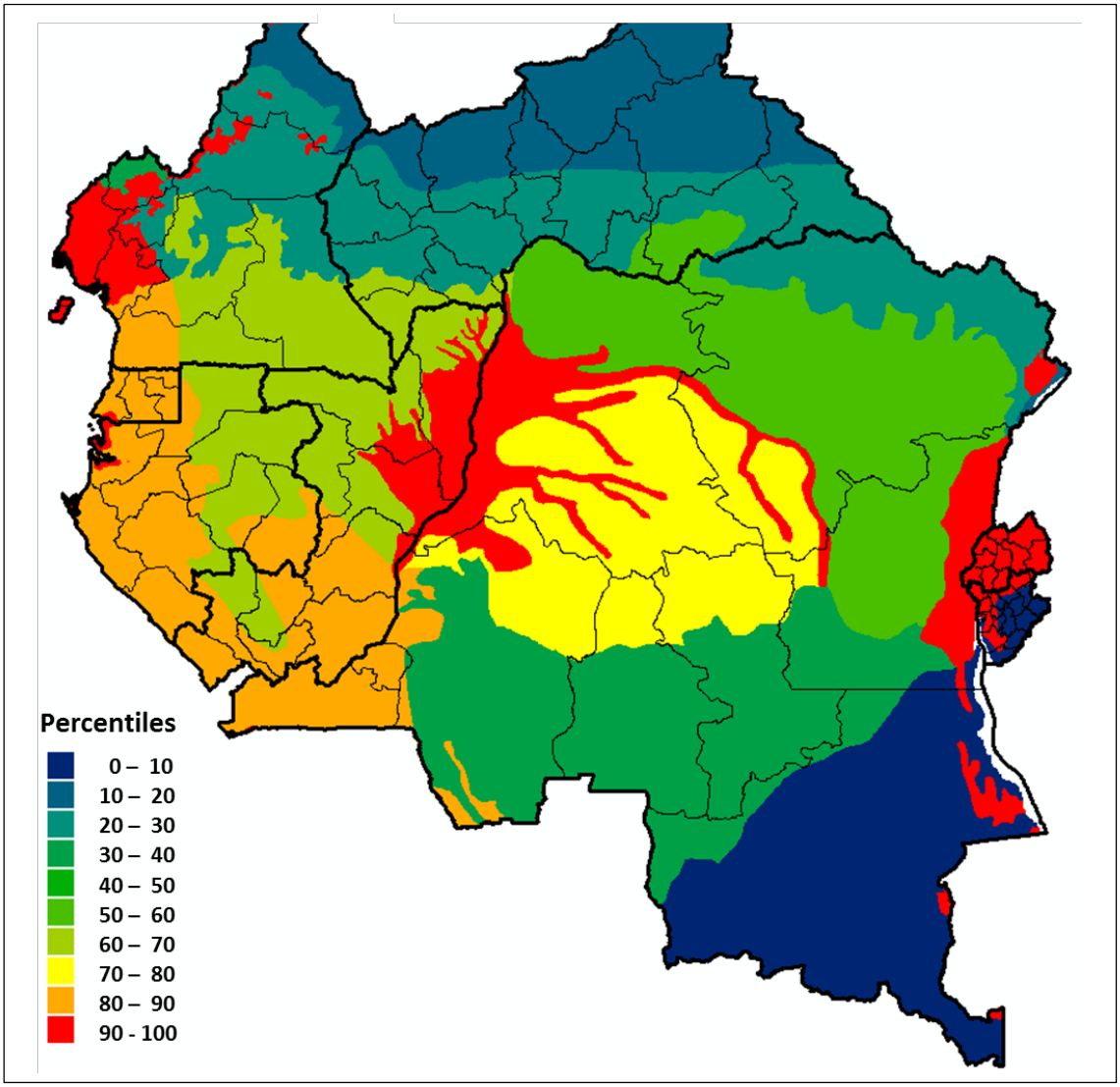
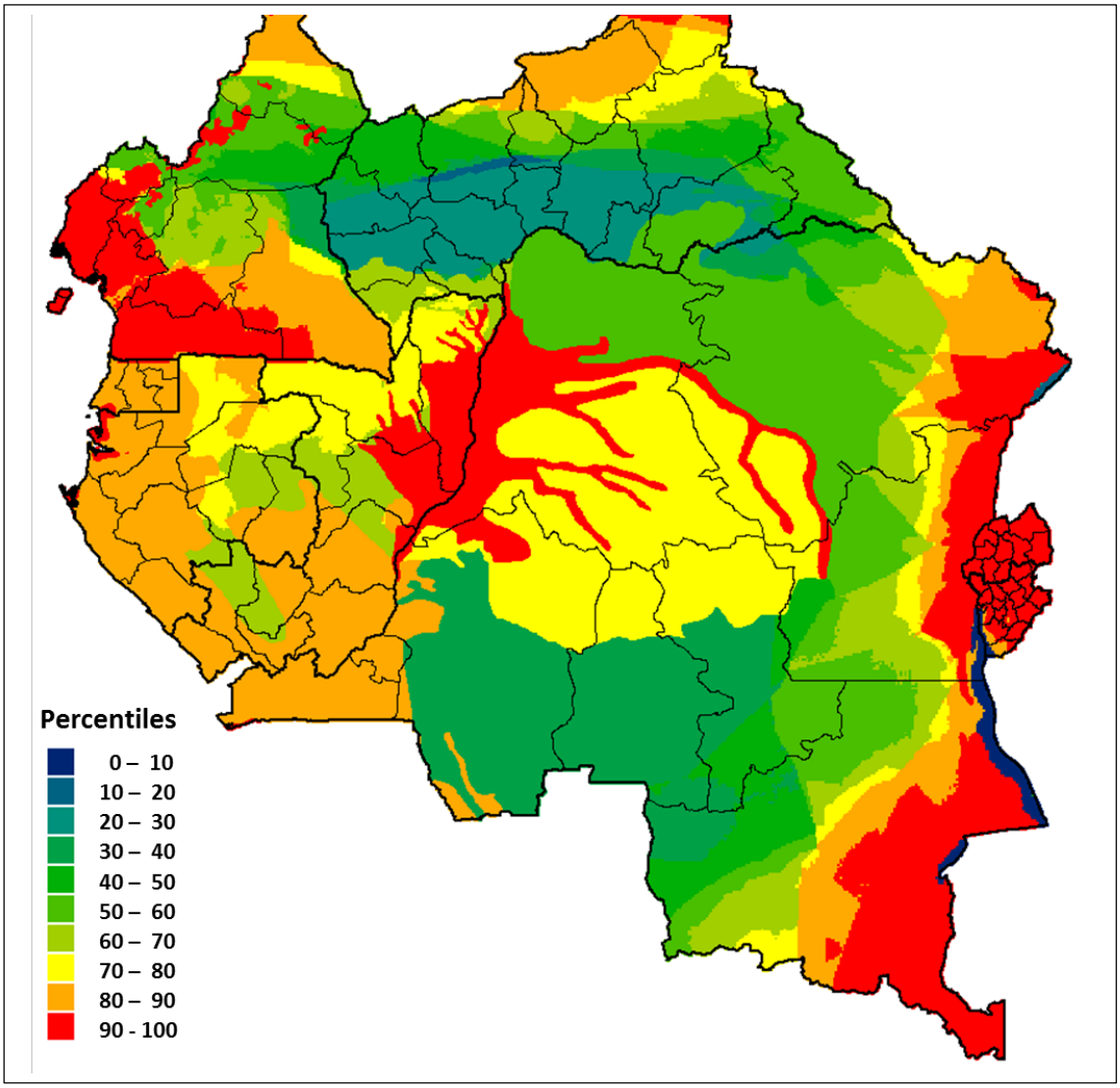


Figure 19: Composite species-ecoregion index, Congo Basin countries



the range 0-10. Nevertheless, even maximum scoring produces a map with a wide distribution of pixel values. One striking feature is the blue/green (0-50) band that arcs from northern Cameroon to eastern DRC and back to southern DRC. Another is the prominent clustering of very high values in western Cameroon, along the border between Congo and the DRC, and along the eastern margin of the Basin.

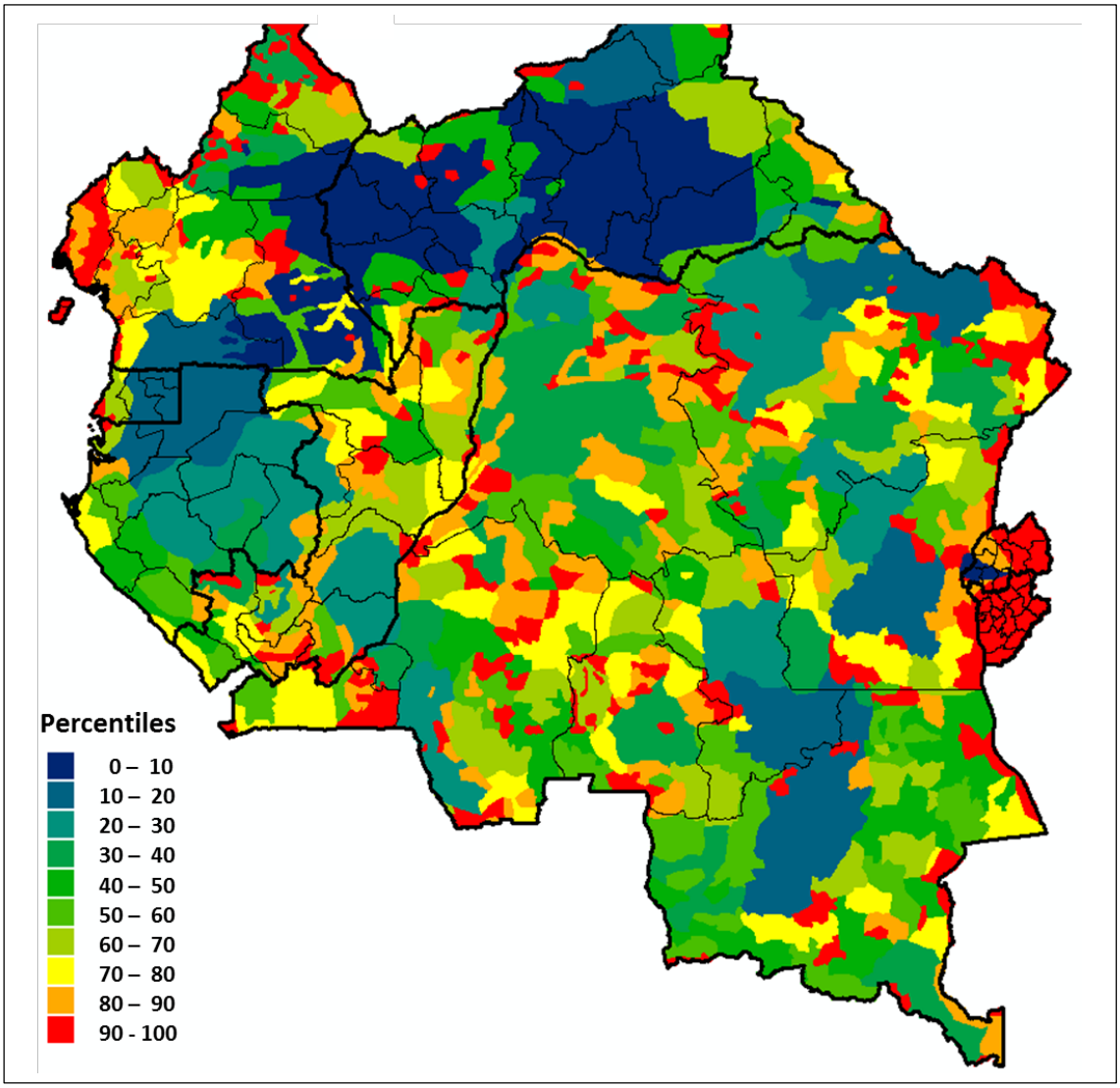
For the purposes of this paper, the most important message in our results is the striking non-uniformity of ecological vulnerability across forested areas in the Congo Basin countries. By implication, a full assessment of the benefits and costs of road upgrading should go beyond simple measurement of forest loss to an assessment of the potential impact of that loss on biological diversity.

8. Ethno-Linguistic Diversity

Within the Congo Basin countries, indigenous territories are occupied by over 500 ethno-linguistic groups. In many cases, their cultures and livelihoods reflect centuries of adaptation to environments that may be altered by forest clearing. Although we focus on biodiversity impacts in this paper, we believe that information about ethno-linguistic domains may also be of interest to infrastructure planners. Accordingly, we construct an ethno-linguistic index that resembles our index for ecoregions. Our data are drawn from Felix and Meur (2001), who have constructed and digitized a map of African ethno-linguistic domains.[11] For the Congo Basin countries, we compute each domain's share of the total area for identified domains. Then we compute a relative sensitivity index for each ethno-linguistic domain as the inverse of its area share. We assign an appropriate index value to each pixel for the Congo Basin countries. This approach assigns higher values to smaller domains, which may be disproportionately affected by forest

[11] The digitized map is available as a shapefile at http://worldmap.harvard.edu/data/geonode:etnicity_felix.

Figure 20: Ethno-linguistic index, Congo Basin countries



clearing. The resulting ethno-linguistic map (Figure 20) is a patchwork pattern of potential sensitivity that only overlaps significantly with the species and ecoregion maps in narrow strips of western Cameroon, eastern DRC, Rwanda and Burundi.

9. Road Improvement Revisited - the Stakes for Vulnerable Areas

In this section, we join the two strands of our research by combining predicted deforestation from road upgrading with our composite index of ecological vulnerability. As we show in Figures 7-9, the multiple determinants of forest clearing can produce highly-varied patterns of road corridor deforestation within the same region. Even more variety is to be expected when we incorporate the vulnerability index, since the correlation between our measures of clearing and ecological vulnerability is close to zero in the database ($\rho = -0.0356$). Our primary expositional task is simplification, since combining the two indicators produces results for thousands of road segments. In this paper, we communicate the general tenor of our results by focusing on the four-province area of DRC that we have featured in Figures 7-9. Full results for the Congo Basin countries are available from the authors on request.

Figure 21 sets the stage by overlaying the road network on a composite vulnerability map for the four-province area in eastern DRC (Kivu, Orientale, Equateur, Kasai Oriental). This provides an immediate sense of potential vulnerability from road upgrading at different points in the network. Some roads pass through high-vulnerability areas for long distances, while others remain within low-vulnerability zones. Figure 9 displays projected forest clearing from road improvement, showing extensive deforestation along many primary arteries and around denser parts of the network.

Figure 22 displays the combined impact indicator, which is the product of predicted percent deforestation from upgrading (Figure 9) and the vulnerability index (Figure 21). We have

standardized the indicator so that its range is 0 - 100. To discern the effect of combining the two indicators, compare Figures 9 and 22 for the dense road cluster south of the Kasai Oriental label. Figure 9 has consistently dark brown areas throughout the cluster, indicating intense deforestation in the road corridors. In Figure 22, however, the southern and western parts of the cluster are dominated by indicator scores in the range 0-10 (yellow), while the central and eastern parts have large clusters in the range 30-100 (red). In part this reflects variation in biodiversity vulnerability, which is relatively low (green) in the southern part of the cluster and significantly higher (yellow) in the northern part.

10. Summary and Conclusions

In this paper, we have used high-resolution spatial data for eight Congo Basin countries to develop and estimate an econometric model of deforestation that incorporates the economics of road improvement. We find large, highly-significant effects of upgrading on the intensity and extent of forest clearing in road corridors. In addition, our results highlight the powerful roles played in proprietors' forest-clearing decisions by market access, land opportunity values, official protection status and topography. They also provide the first estimate of the impact of violent conflict on deforestation in Sub-Saharan Africa.

Using our econometric estimates, we predict the impact of generalized road upgrading on forest clearing along road corridors in the Congo Basin. We illustrate the results with a detailed assessment of impacts in the DRC. Predicted effects in road corridors vary widely with prior road conditions and locational economics, but increases of 10-20% are typical. In addition, many corridors have significant extensions in the outer margin of forest clearing.

Figure 21: Eastern DRC - Road networks and ecological vulnerability

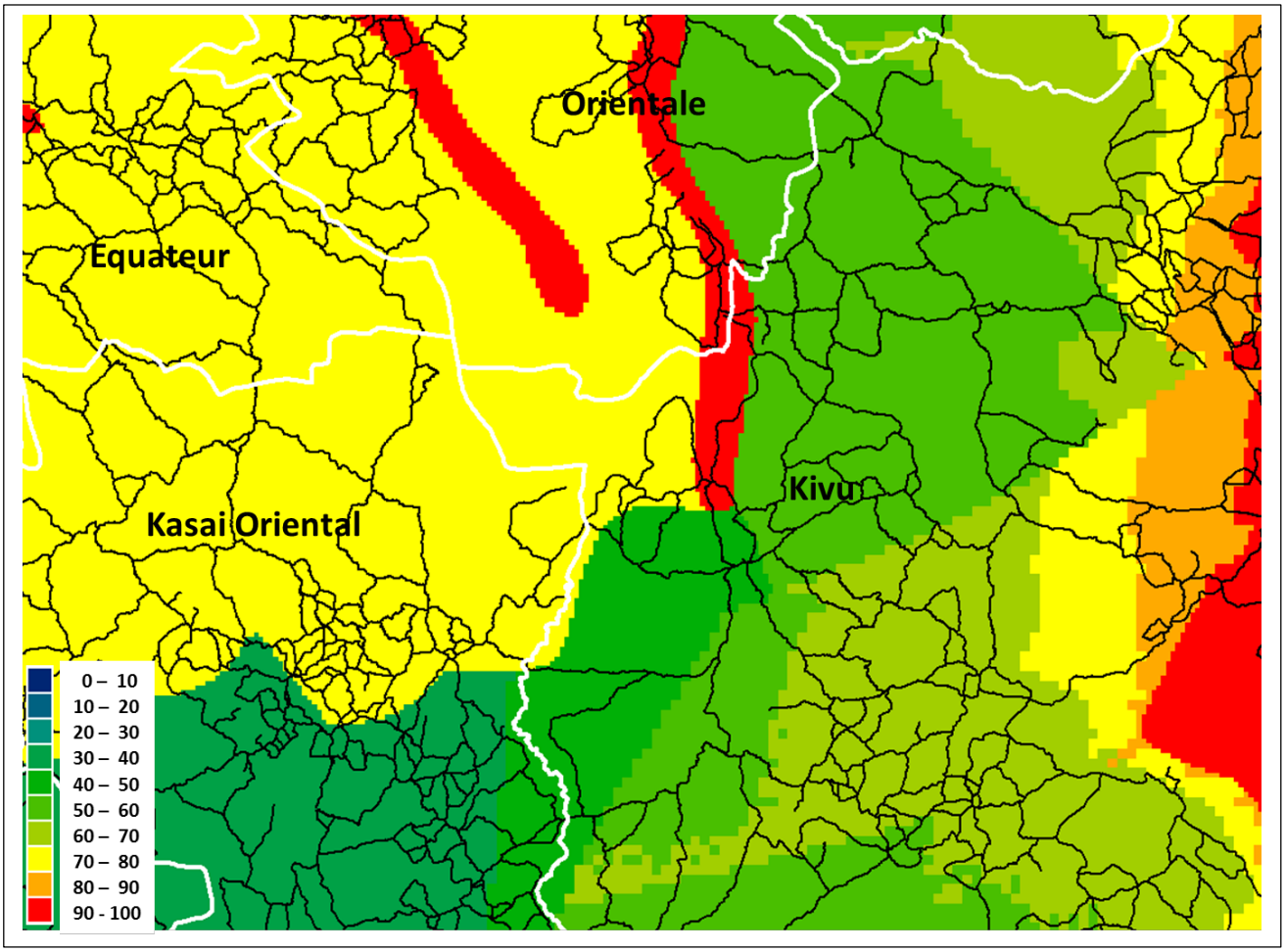
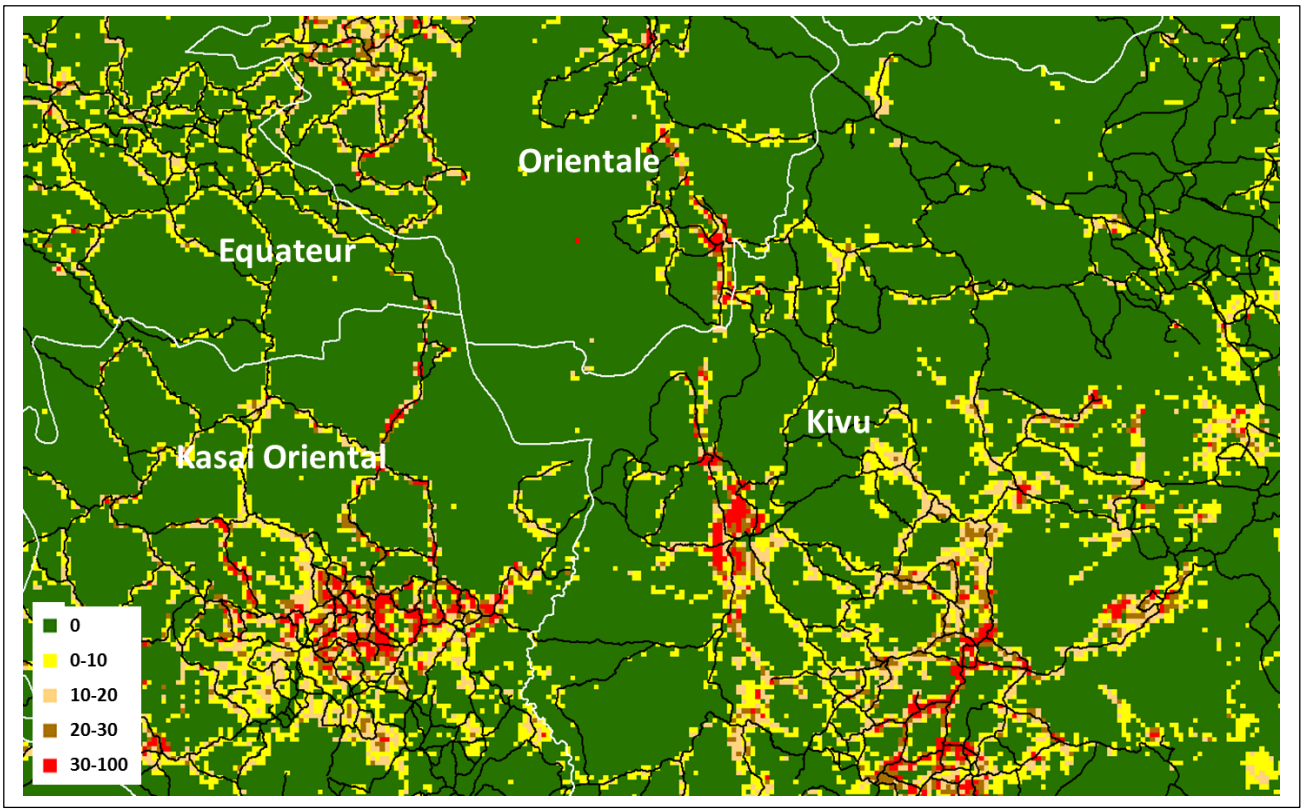


Figure 22: Eastern DRC - Ecological risk from road network improvement



After investigating the impact of road improvement on forest clearing, we extend the analysis to potential ecological impacts. Using spatially-formatted databases from IUCN, BirdLife International and WWF, we construct a pixel-level measure of biodiversity risk for thousands of animal species and plant biomes. The resulting high-resolution map reveals a complex geographic pattern of ecological vulnerability. We overlay the Basin-wide road network on this map to provide a first-order guide to risk assessment for proposed road corridor improvements.

In the concluding stage of the analysis, we combine our ecological risk indicator with pixel-level predictions of forest clearing produced by road upgrading. The result is a high-resolution map of expected risks for road upgrading in road segments, corridors and regional

networks. Predicted deforestation is uncorrelated with our vulnerability indicator, so the variation in the two indicators separately is compounded in the combined measure. We illustrate the implications in a detailed assessment for the eastern DRC.

Overall, our results cast doubt on the utility of generalizations about the impact of road upgrading on deforestation and vulnerable biomes. In our high-resolution spatial assessment, we find impacts as varied as the economic, social and ecological conditions that prevail in different road corridors. However, our results are also cautionary, because we find very large impacts in some road corridors and significant impacts in many more. By implication, road improvement planning in tropical forest regions is unlikely to maximize welfare unless it anticipates and incorporates such impacts.

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Appendix Table: Regression results for DRC (all non-dummy variables in log form)

	(1) OLS	(2) OLS	(3) 2SLS	(4) GLS (IV)	(5) Robust (IV)
Distance from Road	-0.298	-0.309	-0.309	-0.309	-0.296
	(29.97)**	(30.43)**	(30.43)**	(8.80)**	(32.77)**
Protected area x Distance from road	-0.165	-0.204	-0.204	-0.204	-0.152
	(18.56)**	(22.79)**	(22.79)**	(2.91)**	(19.18)**
Road condition	0.544	0.455	0.455	0.455	0.513
	(17.56)**	(13.76)**	(13.76)**	(1.57)	(17.49)**
Transport cost to nearest urban center	-0.481		-0.952	-0.952	-0.876
	(34.15)**		(23.54)**	(3.28)**	(24.39)**
Euclidian distance to nearest urban center		-0.279			
		(23.54)**			
Land opportunity value	-0.091	-0.023	-0.023	-0.023	0.004
	(10.32)**	(2.63)**	(2.63)**	(0.37)	(0.46)
Elevation	-0.066	-0.130	-0.130	-0.130	-0.238
	(2.06)*	(3.97)**	(3.97)**	(0.59)	(8.18)**
Conflict intensity (1997 - 2007)	0.016	0.029	0.029	0.029	-0.000
	(5.52)**	(9.96)**	(9.96)**	(1.23)	(0.10)
D2002	0.935	0.934	0.934	0.934	0.925
	(21.93)**	(21.46)**	(21.46)**	(19.61)**	(23.92)**
D2003	1.269	1.269	1.269	1.269	1.246
	(29.78)**	(29.15)**	(29.15)**	(22.76)**	(32.24)**
D2004	1.559	1.558	1.558	1.558	1.542
	(36.58)**	(35.81)**	(35.81)**	(27.75)**	(39.91)**
D2005	1.827	1.826	1.826	1.826	1.810
	(42.87)**	(41.97)**	(41.97)**	(32.71)**	(46.86)**
D2006	1.983	1.982	1.982	1.982	1.972
	(46.56)**	(45.58)**	(45.58)**	(36.81)**	(51.07)**
D2007	2.155	2.154	2.154	2.154	2.145
	(50.59)**	(49.52)**	(49.52)**	(38.55)**	(55.55)**
D2008	2.278	2.278	2.278	2.278	2.271
	(53.50)**	(52.37)**	(52.37)**	(40.65)**	(58.81)**
D2009	2.462	2.462	2.462	2.462	2.456
	(57.81)**	(56.60)**	(56.60)**	(44.19)**	(63.62)**
D2010	2.651	2.650	2.650	2.650	2.647
	(62.25)**	(60.94)**	(60.94)**	(48.34)**	(68.56)**
D2011	2.747	2.746	2.746	2.746	2.738
	(64.50)**	(63.14)**	(63.14)**	(48.95)**	(70.92)**
D2012	2.832	2.831	2.831	2.831	2.821
	(66.48)**	(65.09)**	(65.09)**	(49.73)**	(73.06)**
Constant	4.810	4.806	6.747	6.747	7.255
	(23.39)**	(22.07)**	(25.94)**	(4.07)**	(31.42)**
Observations	13758	13758	13758	13758	13758
R-squared	0.49	0.47	0.47	0.47	0.51

Absolute value of t statistics in parentheses
*** significant at 5%; ** significant at 1%**