Population pressure and global markets drove a decade of deforestation in Africa’s Albertine Rift

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Abstract

Africa’s Albertine Rift faces a juxtaposition of rapid human population growth in a biodiversity hotspot. Using satellite-derived forest cover change, we examined national socioeconomic, demographic, and agricultural production data, and local level demographic and geographic variables, to assess multilevel forces driving significant local deforestation outside protected areas over the first decade of the 21st century across six countries in the Albertine Rift. Deforestation rate varied by country, driven by increasing national population, production of tea and beef, and increasing GDP. Population change was the strongest driver - a doubling of national population was predicted to cause 7.26% annual local forest cover loss, while doubling tea and beef production was predicted to cause 1.69% and 1.04% annual deforestation, respectively. We found a small, but significant, reduction in deforestation with increasing distance from protected areas, supporting studies showing higher rates of landscape change near protected area boundaries. Significant deforestation correlated to lower local population density, an apparent contradiction consistent with findings that larger scale forces outweigh local drivers of deforestation. This implicates demographic and market forces at national and international scales as critical drivers of change, calling into question the necessary scale of forest protection policy in this biodiversity hotspot.

Keywords: Deforestation; biodiversity hotspot; protected areas; demographic pressure; Africa; Albertine Rift.
Introduction

The Albertine Rift region of Africa, comprising parts of Uganda, Tanzania, Burundi, Rwanda, the Democratic Republic of Congo (DRC) and Zambia, is a biodiversity hotspot (Plumptre et al. 2003, 2007), containing several large and many small protected areas (Figure 1). The juxtaposition of some of the highest human population growth rates and densities in the world, and richest conservation areas, make it one of the world’s most vulnerable conservation-poverty hotspots (Fisher and Christopher 2007). One of the biggest concerns about the increasingly isolated protected areas in the region is the pressure exerted by external deforestation and demand for arable land by a rapidly increasing and dense rural human population (Hartter and Southworth 2009, Hartter et al. 2011). While rural poverty and local population pressure are often cited as reasons for deforestation in developing countries (Sassen et al. 2013), reviews suggest that the evidence does not support it (Rudel 1996), and instead, multiple levels of socioeconomic and political forces at local, national and global levels operate to determine deforestation (Geist and Lambin 2002, Meyfroidt et al. 2010, Lambin and Meyfroidt 2011).

The forest transition theory (FT), predicts that as GDP increases, corresponding to development, deforestation due to agricultural conversion accelerates, then plateaus, and finally starts to decrease (Lambin and Meyfroidt 2010, 2011, Meyfroidt et al. 2010). Rather than increasing poor rural populations driving deforestation, large scale human migration patterns associated with urbanization may deplete the rural population, leaving marginal lands to recover, suggesting areas of reforestation (Aide and Grau 2004, Grau and Aide 2008, Aide et al. 2013). However, an increasingly urban population may also place higher demand on rural fuelwood economies (Mackenzie and Hartter 2013), creating a counterintuitive signal of population density and deforestation. These FT theories and extensions have not been tested in Africa, to our
knowledge, and instead derive from studies in other regions, such as the Amazon. In the Albertine Rift, both national and sub-national population trends over the first decade of the 21st century may have been influenced by armed conflict, rural-urban migrations, climate impacts, and global market forces influencing national commodity and monetary flows (DeFries and Rosenzweig 2010).

The Albertine Rift has experienced considerable conversion of land to agriculture, from extremely small-scale multi-cropping subsistence agriculture, fragmenting and subdividing rural landscapes around protected areas, to cooperative scale farming for tea (Hartter and Southworth 2009). While larger scale farming does not approach the magnitude of developed nations’ corporate monocropping, it nonetheless results in substantial and lasting conversion of the landscape (Hartter and Southworth 2009, Hartter et al. 2011, Ryan and Hartter 2012). Although tropical forest conversion for meat production is well known as an Amazonian frontier problem (Alves et al. 2009), an increasingly affluent and urban population, driving higher meat consumption, likely also impacts the Albertine Rift.

We randomly sampled 100,000 points across the Albertine Rift to analyze forest cover (percent canopy cover) derived from moderate resolution satellite imagery (MODIS) from 2000-2010 to quantify forest change at a 250m resolution. Ten annual estimates of canopy cover were used to develop linear regressions for each point. We examined locations with significant rates of forest loss over the decade, and analysed these in a hierarchical model to simultaneously assess the impacts of local and national level drivers on local forest change. We examined the relationship between small-scale, local forest cover change and potential demographic, economic, and agricultural production drivers of deforestation at the local and national level for the six countries that constitute the Albertine Rift.
The Albertine Rift contains over 100 large protected areas, and also many important lakes (Figure 1). Human settlements occur near lakes, independent of forest cover. Thus, we allowed the distance from water to vary randomly in the model across countries, controlling for the heterogeneity of landscape distances from water. Our local level population density data derives from the African part of the most recent WorldPop dataset (Linard et al. 2012), which overcomes the problem of sparse and outdated population census data in Africa, by combining satellite derived settlement information with census data.

Methods

Data acquisition and processing

We sampled the Moderate Resolution Imaging Spectroradiometer (MODIS) data derived product, VCF (Vegetation Continuous Fields - MOD44B, 250m resolution) with 100,000 spatially random points across the Albertine Rift. Regressions for each point were used to derive a slope of annual forest cover change between 2000 and 2010 using ten annual estimates of percent forest cover (Hansen et al. 2005). Only significant regressions were used (at $p \leq 0.05$, $n=8,175$), and we removed all points that fell inside protected areas (1,333), and those classified as ‘reforestation’ (positive slopes, $n=2,685$), yielding a dataset of spatially random deforested points ($n=2,685$). We note that using MODIS-derived forest cover change may miss small scale deforestation (less than 250 m) and that the Vegetation Continuous Fields often has annual fluctuations and errors. The advantage is that this MODIS product allows for sub-pixel proportional estimates of tree crown cover and provides an estimate preserving a continuous variable of landscape heterogeneity.
We controlled for the potential impact of large water bodies by including distance to water as a random intercept in the multilevel model. Our ‘local’ per pixel population density change estimates were derived from the 100m resolution WorldPop (Afripop) dataset (Linard et al. 2012), aggregated to 250m resolution, and log transformed prior to centering. Agricultural and market production measures (tea, maize, meat, in tonnes for countries from 2001-2010 were acquired from the Food and Agricultural Organization (FAO) (faostat.org, accessed May 15th, 2013), and demographic and economic variables for 2001 and 2010 (population, rural proportion, GDP) were acquired from the World Bank (data.worldbank.org, accessed May 15th, 2013). These were all included in models as proportional changes. All independent variables were centered in the models to facilitate convergence and interpretation. Using multi-model selection, we constructed and selected the best fit hierarchical model to simultaneously assess the impacts of local and national level drivers of local forest change.

Analysis

We used multilevel models in R (version 2.13.2; packages ‘lme4’, ‘arm’, glmulti) to explore the roles of demographic and environmental change at the local, pixel level, and the additional roles of market forces at the country level. There are many languages used to describe multilevel, hierarchical, mixed effects, or nested models, which vary between and even within disciplines. For ease of explanation, we refer to this regression as a multilevel model, and describe the variance components as they appear in our specific case.

We used a basic two-level model, allowing slopes to vary across groups, to describe the significant slope of forest cover change, $y_{ij}$, at the pixel level ($i$), within country ($j$):

Level 1: $y_{ij} = \beta_{0j} + \beta_{1j}(X_{1ij}) + \beta_{2j}(X_{2ij}) + \ldots + \beta_{nj}(X_{nj}) + e_{ij}$

\text{eqn.1}
Where $X_{1 \ldots n}$ are predictor variables at the pixel level; $e_{ij}$ is the error term subsuming the independent error term for the intercept $\beta_0$ and the independent error of the regression coefficients $\beta_1$ to $\beta_n$, and the predictors $X_1 \ldots X_n$. $\beta_0$ to $\beta_n$ are the regression coefficients, whose variation depends on explanatory variables at the country level, for example:

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + \mu_{0j}$ \hspace{1cm} eqn. 2

In which $\gamma_{00}$ is the intercept for the overall model of $\beta_0$, and $Z_j$ is the country-level predictor, with the residual error $\mu_j$ at the country level.

As we had multiple local and country level predictors, this can be summarized with $X$ taking subscript $p \ (1 \ldots P)$, and $Z$ taking $q \ (1 \ldots Q)$, as:

$$Y_j = \gamma_{00} + \sum_p \gamma_{pq}X_{pj} + \sum_q \sum_p \gamma_{pqz}Z_{qj} + \sum_p \sum_q \gamma_{pqz}X_{pj}Z_{qj} + \sum_p \mu_{pj}X_{pj} + \mu_{0j} + e_{ij}$$ \hspace{1cm} eqn. 3

As our hypotheses included predictors that are likely to be correlated, we mean-centered all variables (described below) and also examined variance inflation factors (VIFs) of the parameters and kappa statistics for collinearity effects on the overall model.

For most predictor variables, we used proportional changes in the indicators, and centered the variable. Centering predictors is useful to interpretation in multi-level models by allowing examination of relative change on the mean (average) property of a level at the higher level. Additionally, it helps reduction of collinearity effects on estimates, and tends to improve model convergence. For population density change, we subtracted 2000 density from 2010 density and transformed the predictor ($\ln(x+1)$), for stability in the model. Distance to parks was a continuous variable that did not change over decade, so was used in its raw form, centered.

We conducted predictor selection by examining the variables used at each level in a multi-model comparison using Akaike’s Information Criterion (AIC) to select the best candidate set of
variables (Burnham and Anderson 2002), using the R package ‘glmulti’ (Calcagno and de Mazancourt 2010).

The base (or intercept only) model $y_{ij} = \beta_{0j} + e_{ij}$, was used to establish the structure accounted for in the data at the country level, to compare the impact of adding predictors at the two levels (pixel ($i$) and country ($j$)). We created a baseline model for negative slopes (deforestation), and derived AIC values, using maximum likelihood estimation in R. We then stepped through two stages of predictor and factor addition: adding a random component to the model, both country and then the distance to water; then using model selection for the fixed component on the remaining predictors at the country and pixel level. In each stage, model improvement over the previous was assessed, with the criteria of ‘improvement’ at $\Delta$AIC $\geq 2$ (Anderson et al. 2001, Burnham and Anderson 2002).

For the best model fits, for ease of interpretation, we assessed significance of parameters using t-tests, assuming that our large sample size (2,680) and relatively few estimated parameters (6) obscured the uncertainty about estimating degrees of freedom (DF), which would exceed 500, often the point of reported convergence of the critical value at 1.96 for $\alpha=0.05$. We also constructed quasi-$R^2$ measures of model fit as the $R^2$ from a linear regression of the predicted and observed model, obtained from R package ‘lme4’, recognizing that mixed model structures do not lend themselves to true $R^2$ values.

**Model stability**

When we examined the final models for collinearity, using the Kappa statistic (‘mer-utils.R’, https://github.com/aufrank/R-hacks.git), we obtained value of $\kappa= 4.94$, suggesting low collinearity. We calculated variance inflation factors (VIFs) to assess all predictors, and found that our centered GDP predictor had a VIF=5.22 suggesting some inflation. As all other
predictors had VIF less than 5, there was no reason to exclude GDP from the model, as this was unlikely to cause problems in estimates of model fit (Gelman and Hill 2006).

**Interpreting the importance of predictors**

In the multilevel models, we examined the fixed effects for significance. Predictors that proved significant in our multilevel model are shown in bold in Table 1. The resulting predictors are a measure of percent rate of annual change of woody vegetation (forest) cover as a result of proportional changes in the predictors, except distance to protected area, which is a continuous measure of distance, and population density, which is a log-transformed difference. The former is best interpreted in terms of a doubling effect of the predictor. In the deforestation model, the response is necessarily negative – a negative value on the predictor indicates a loss of forest cover.

**Results**

There was considerable variation between countries in the rate of significant local deforestation (-1.98% mean annual cover loss) from 2000-2010 within our sample (Figure 2). Thus a multilevel modeling approach is necessary to understand the simultaneous impacts of national and local processes. We compared models of all possible subsets of independent variables in the fixed component, using Akaike’s Information Criteria (AIC) with a threshold of $\Delta AIC > 2$ for model differentiation (Anderson et al. 2001, Burnham and Anderson 2002). We included national meat (beef, veal) production, national maize production, national tea production, GDP, national total population, the proportion of rural population, local population density and the distance to nearest protected area as independent variables, derived from FAO and World Bank data.
Model Fits

The simple model of deforestation by country was our base model (AIC=7,125). Adding the distance to water component to the random effect improved the model fit considerably (AIC = 7,042, ΔAIC = 117). We then performed model selection by testing all possible sub-models with our fixed component, arriving at the top model (Table 1), with AIC=7,029 (ΔAIC=13), demonstrating improvement in support. The best fit model for deforestation included national total meat and tea production, national population change, GDP, local population density, and distance to protected areas, as drivers of deforestation (Table 1).

Discussion

Deforestation signals in the first decade of the 21st century across the Albertine Rift suggest that landscapes surrounding protected areas are threatened from the ongoing processes of land conversion and fragmentation outside their boundaries. We found a small (4.4 x 10^-6 % per year), but significant, trend of declining deforestation rate as the distance from protected areas increased, across six countries. The process of increasing isolation of remnant forest cover continues to challenge protected area management, indicating a need to understand and manage drivers of deforestation.

National level population change was the biggest driver of deforestation; a doubling in population is predicted to cause 7.26% annual forest loss at the local level. In Uganda, which has a population growth rate of 3.3% (United Nations 2009), population doubling would occur in 21.35 years. The increase in population across the Rift will put ever more pressure on remaining forests for fuelwood, timber for housing, and other resources, in addition to land clearing for agriculture.
At the local level, an increase in population density was associated with lower deforestation. While this seems contradictory, it supports recent work suggesting that local population pressure is not a main driver of deforestation (DeFries et al. 2010). In sub-Saharan Africa, rural livelihoods depend on land and natural resources (Abulu and Hassan 1998); increasing population growths, and a trend towards middle-income economies is placing ever-increasing pressures on land use and natural resources (Hartter and Ryan 2010). Corresponding to FT theory, a rising GDP was significantly associated with less deforestation over the decade, although the effect was small. This suggests that the coupled forest transition and development spectrum are not restricted to Latin America and the Caribbean, and point to the need to understand how development, land tenure legislation, and population growth will proceed in conjunction with forest and timber trade policies at multinational scales.

The increase in production of both tea and meat at the national level were found to be drivers of local deforestation, responsible for 1.69% and 1.04% annual forest loss with a doubling in production. These two markets may operate in different ways to exert this change. Tea is largely produced for global export markets (Chapagain and Hoekstra 2007), exported to, and departing from Kenya (FAOSTAT.org, accessed May 15th, 2013), while meat produced in the countries of the Rift is largely traded within sub-Saharan Africa (FAOSTAT.org, accessed May 15th, 2013). While tea production was initially a holdover from colonial land ownership and markets oriented toward supporting Great Britain, it clearly continues to be a major market force in the region. Tea transforms the landscape by introducing a perennial crop, rather than seasonal subsistence level crops, requiring larger land parcels, added transportation infrastructure, and fuelwood for drying. It also transforms the scale of economy, as tea businesses may induce cooperatives, requiring a steady labor force. Potentially of significance for biodiversity
maintenance, in a region where almost no chemical fertilizers are used, tea is heavily fertilized (Freeman and Omiti 2003), adding potential ecotoxicological impacts on landscape health.

As protected area management and human livelihoods continue to exert impacts on the landscape of the Albertine Rift, it is important to identify the driving forces behind deforestation, as this information is needed to guide conservation strategies. While the best fit model demonstrated the importance of these multilevel drivers, the quasi-\( R^2 \) calculated for this model is 0.22, suggesting that there are further factors to explore to explain the full variance in deforestation across this hotspot. We found that national production markets for both meat and tea are significant drivers of deforestation, but serve different scales of consumers. Tea is meeting a global demand, whereas meat production is meeting regional dietary shifts towards higher meat consumption in more affluent urban areas. Population growth and GDP were also very important drivers, and far more complicated to address as conservation policy. Targeting policy at the appropriate scale to protect forest cover, and identifying the scope of population pressure on remaining fuelwood supplies is fundamental to protecting this biodiversity hotspot.

Acknowledgments

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Author Contributions

SJR conceived the framework, conducted statistical analysis; MP processed data and contributed to analysis; SJR, MP, JED, CAC and JH wrote the manuscript.
Table and Figures

Table 1. Parameter estimates and significance ($p$-value) for the best fit model of significant deforestation across the Albertine Rift, Africa.

Figure 1. The Albertine Rift region of Africa. Note lakes and protected areas. This figure was produced using ArcGIS 10 (ArcGIS 10 1999).

Figure 2. Significant deforestation rates 2001-2010 (% cover/yr) ($n=2,685$), in six countries, outside protected areas and water bodies in the Albertine Rift, across a geographically random sample of 100,000 points. Boxes encompass 95% confidence intervals of the mean, while whiskers contain the 25-75% quantiles of the data. The rates varied significantly across the countries (ANOVA: $df=5, 2674$, $F=108.3$, $p<0.001$).

Figure 3. The individual partial effects of the predictors in the top model (with 95% confidence interval bands in grey): a. distance from protected areas (m); b. population density; c. GDP proportional change; d. tea production change; e. beef production change; f. national population size change.
Table 1:

<table>
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<th>Model variable</th>
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<td>Total Population</td>
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<td>Meat Production</td>
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<td>Tea Production</td>
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<tr>
<td>Distance from nearest park</td>
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<td>0.00</td>
</tr>
</tbody>
</table>

*% annual forest cover loss
Figure 2
References


31  Environmental Systems Research Institute, I. *ArcGIS 10*, 1999-2013.)