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Examining Connections between Gendered Dimensions of Inequality and Deforestation in Nepal

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Introduction

Gender equality is one of the most important components of a sustainable future for the planet. The UN recognizes this, with "Achieve gender equality and empower all women and girls" as number five on its list of 17 sustainable development goals (UN, 2015). Despite the UN's consensus on this, globally (UN, 2015):

- Approximately 20% of all women have experienced sexual/physical violence by a partner *within the last 12 months*
- Women spend about 2.5 times as much time on unpaid or informal labor as men
- Only 23.7% of national government parliament members are women
- Women only make up only 13% of agricultural land holders
- About 30% of female employment is in agriculture

During my time at UVM I became acutely aware of gendered issues as they exist on college campuses – from men talking over women constantly in classes, to addressing sexual violence in residence halls as an RA. The social structures surrounding our gender identities are inescapable and affect our behavior as individuals deeply (myself included). Gender inequalities exist and persist because of these behaviors. I take a normative stance following the UN (and what I personally believe in) in suggesting that *a gender equal world is a better world for all*. Aside from being morally just in my eyes, it is also increasingly evident that empowering women improves the lives of all, not just women – it improves childhood health, increases food security, mitigates sexual disease spreading, and reduces poverty, among other things (Black et al., 2008; Chowdhury et al., 2013; Fisher & Naidoo, 2016; Smith, Khan, Frankenberger, & Wadud, 2013). It is also of interest to various international conservation and develop organizations how gendered norms relate to environmental outcomes, especially in rural, agraricultural areas (Deda & Rubian, 2004; Rocheleau & Edmunds, 1997). Because of how women in these areas are often disproportionately affected by environmental change, it is important to understand how gender relates to both environmental management processes and outcomes (Denton, 2002). In this undergraduate thesis, I aim to quantify and evaluate the relationship between deforestation and gender inequality as it relates to agricultural land ownership at the community scale.

To conduct this analysis, I focus on Nepal, a country active in the UN's Reducing Emissions from Deforestation and forest Degradation program (REDD+), and a place where most of the rural population depend on forests for subsistence needs (Khadka, Karki, Karky, Kotru, & Darjee, 2014). Additionally, Nepal has a rich and interesting history of community-based forestry and subsistence living. As of 2013, there were approximately 18,000 community forest user groups (FUG) there, representing about 40% of the population (Das Shrestha, 2013). Despite this large group of active users, and despite women disproportionately using forest products for sustenance, only about 5% of FUG leaders were women (Das Shrestha, 2013; Lama, Kharel, & Ghale, 2017). This begs the question as to whether women having agency over land reduces environmental degradation. I use this as a motivating question to help guide the mapping, modeling, and descriptive statistics I use in this paper.

Literature Review

The Roles of Women in Natural Resource Management (NRM)

It has long been recognized that empowering women plays a crucial role in meeting a wide range of goals relating to the sustainable use of natural resources (*The Rio Declaration*, 1992). The roles that women play in meeting these goals vary greatly across sociocultural and environmental contexts, but are universally recognized by the UN as key to long-term global sustainability (*Gender in Agriculture Sourcebook*, 2008; UN, 2015). Given a growing body of evidence suggesting that women may provision natural resources differently (and possibly more efficiently) than their male counterparts, empowering women and addressing gender inequity is increasingly seen as a critical component of conserving biodiversity, promoting food security, and mitigating environmental conflict (B. Agarwal, 2000; *Gender in Agriculture Sourcebook*, 2008).

While the empowerment of women is recognized by the UN as being critical for sustainable development, the degree to which this is implemented at the community scale is highly heterogeneous and reflects different sociocultural and environmental contexts (B. Agarwal, 2000; Fisher & Naidoo, 2016; Nations, 2015). Women's participation rates in land-use decision-making, their access to natural resources, and their specific roles in activities that impact the local landscape are all important facets of gender inequality that vary at the local level to an extent that makes national-level policy-making almost obsolete in some cases (Coulibaly-Lingani, Tigabu, Savadogo, Oden, & Ouadba, 2009; Deda & Rubian, 2004). These factors vary in accordance with social norms, traditional land tenure regimes, and formal land-use laws, in addition to the degree of dependence that a community has on local natural resources (Coleman & Mwangi, 2013; Coulibaly-Lingani et al., 2009). For example, women in Burkina Faso are likely to cite traditional land tenure regimes (*de facto*) as a constraint to their access to forest resources, whereas men are more likely to cite formalized laws (Coulibaly-Lingani et al., 2009). In the same study area, women and men were found to have divergent roles in the utilization of non-timber forest products (NTFPs) as well – men and women were found to have equal participation rates in the harvesting of NTFPs, but women were more involved in processing them for sale or consumption (Coulibaly-Lingani et al., 2009). Another study found that women in rural areas (who often disproportionately rely on local natural resources for basic necessities such as firewood and food) are directly impacted by community resource regulations yet have relatively little agency over how these decisions are made (B. Agarwal, 2010). This disconnect in decision-making and gender equity is present more often than not in subsistence-based communities and is reflected in studies on gender equity and resource use around the world (B. Agarwal, 2000; Crawford, 2012; Deda & Rubian, 2004).

There is also evidence that suggests there are gendered differences in intra-household resource allocation efficiency across male- and female-headed households due to input choices relating to the traditional labor roles (i.e. women are expected to care for children, cook, etc., whereas the role of men is often more specialized). However, these conclusions vary greatly with sociocultural, and economic context (Quisumbing, 1996).

While it is difficult to statically categorize the variation in community-scale roles of women in NRM due to external influencing factors, there have been numerous attempts to identify the conditions that facilitate more gender-equitable NRM schemes. For example, in one cross-country analysis, community forestry groups that had less economic inequality, a smaller gender pay-gap, better access to education, and histories of female participation in community forestry all had statistically significant improved rates of female leadership in NRM (Coleman & Mwangi, 2013). Separate studies in rural India and Nepal found that increased participation rates of women in community forestry groups lead to women being more outspoken in the decision-making process, suggesting that the factors outlined by Coleman and Mwangi can directly affect management outcomes to more equitably incorporate the perspective of women (B. Agarwal, 2010). Aside from encouraging women to participate in local governance structures, gender equity can also be addressed by strengthening land tenure for women.

The Gender Roles of Land/Forest Tenure in Subsistence-based Communities

In most developing countries land is a critical household asset and a signifier of wellbeing (Fisher & Naidoo, 2016; Goldstein, Houngbedji, Kondylis, O'sullivan, & Selod, 2015; Jayne et al., 2003; Katz, 2010). Property rights can thus act as a barrier or access to formal and non-formal market institutions, such as community governance structures or agricultural markets (Katz, 2010). Additionally, land often acts as a bearer of direct economic value by producing agricultural products, being available for rent or sale, or being used as collateral for credit (Katz, 2010). When women have tenure over the land they reside on, they are empowered to have greater control of a greater share of their household income (especially if the household relies on agriculture or NTFPs for subsistence) (Yngstrom, 2010). With regard to forests in subsistence-based communities, management is often regulated by some combination of *de facto* (self-governing by the users of the resource) and *de jure* (enforced by government) rights (Schlager & Ostrom, 1992). In a case study in Nicaragua, Katz and Chamorro (2002) suggest that land tenure regimes that empower women directly lead to women earning more in labor markets, sharing more financial responsibility in the household, and gaining better access to credit (2002). However, rights to land use vary dramatically based on context, so empowering women by strengthening property laws is not so straightforward in practice.

Gendered aspects of land tenure do not only pertain to formalized land and property rights. For example, in Gambia, women are often entitled to have their own plots to farm rice that are held within a family holding (Carney, 1998). These customary property rights, even though they lack legal tenure, must still be acknowledged if land use change is proposed (Rocheleau & Edmunds, 1997). Additionally, there can be gendered use rights to specific forest resources, as is the case in parts of Kenya. In such cases, women generally have informal withdrawal rights to the fruits and firewood of trees on male-owned land, which signifies that formal ownership does not always reflect use or alienation rights in practice (Rocheleau & Edmunds, 1997). This complicates the possibility to study community-scale forest governance structures, as the tenure over different forest resources (NTFPs, timber) are gendered based on sociocultural context. In such a case in India where women were involved in formal forest resource governance, they were more likely to promote conservation of forestland to sustain NTFP availability due to the gendered nature of the usufruct (the right to use and benefit from the resources of the land) (Bose, 2011). In the same study area, when traditional tribal land rights were re-recognized by the federal government in the form of local executive land-use decision-making committees, women largely lost their management rights to the land, as the federal recognition of indigenous land rights did not take into account intra-ethnic barriers to equitable management (Bose, 2011).

Ali, Deininger, and Goldstein (2014) suggest that delineating property rights and regularizing land tenure (i.e. encouraging property to be delineated by *de jure* rights) lowers the transaction costs of land transfers, meaning that those who hold ownership are better positioned to use land as a means of bargaining, rather than a source of conflict. Empirical studies in Ethiopia and Rwanda found that the formalization of land tenure let households make longer-term investments in their land, with marginal economic benefits being much greater for female-headed households (whose tenure security marginally increased much more than male-headed households, on average) (Ali, Deininger, & Goldstein, 2014; Goldstein et al., 2015). This approach, while successful in many contexts, tends to underplay the complementarity and informality of the roles that many women play on male-owned lands (Yngstrom, 2010). A prominent critique of regularizing property rights claims that this would inherently favor men by not recognizing the roles that women play on the agricultural landscape, which are often characterized by withdrawal and management, but not full ownership (Yngstrom, 2010). This occurred for non-married women in Rwanda, where a tenure-normalization policy was introduced and non-married women subsequently lost land tenure security (while married women *gained* tenure security) (Ali et al., 2014). While both *de facto* and *de jure* rights are important for the long-term viability of decentralized forest governance, they remain to be fully incorporated into the UN's stated goals for the sustainable use and conservation of forests (UN, 2017).

Underlying Socio-cultural Drivers of Deforestation/Forest Degradation

Identifying drivers of land use and land cover change is a primary goal of international development organizations and social scientists, and is a stated goal of the UN in order to promote climate change mitigation as outlined in the REDD+ program (Geist & Lambin, 2001; UN, 2017). In a meta-analysis of studied drivers of forest loss in the tropics, Geist and Lambin identified three intertwined, albeit differentiated, categories to classify drivers (figure 1).

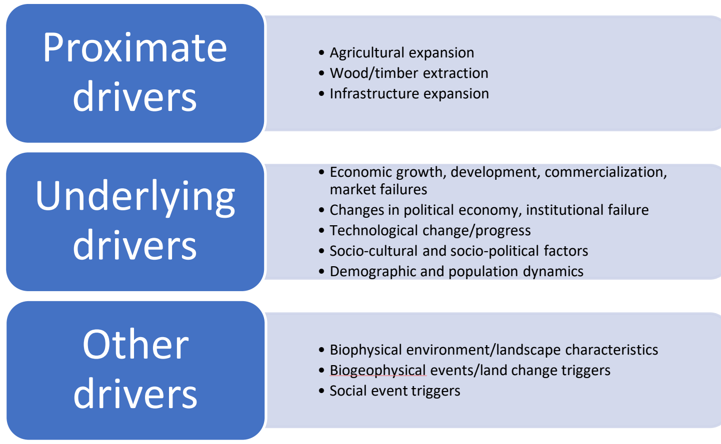

figure 1. Broad typology of drivers of deforestation. Adapted from Geist and Lambin (2001).

These three groups of factors interact as complex systems and are contextually unique, making the degrees of their respective influence difficult to isolate in space and time (Lim, Prescott, Alban, Ziegler, & Webb, 2017). For example, regional differences in agriculture styles (e.g. subsistence agriculture vs. commercial agriculture) and forest resource uses (e.g. subsistence vs. commercial uses of NTFPs and timber) change the institutional and economic scales at which interventions might help conserve forests (Hosonuma et al., 2012; Kissinger, Herold, & Sy, 2012). Spatial heterogeneity in these patterns at the regional, national, and community scales, makes identifying universal causal relationships between underlying causes particularly difficult and sometimes problematic (M. Bhattarai & Hammig, 2001; Kissinger et al., 2012; Rudel, 2013).

Developing countries often have economic and sociocultural conditions that necessitate subsistence use of forest resources, so drivers of deforestation and degradation in such countries are largely functions of aggregate household-level land use choices (fuelwood collection, subsistence agriculture, land tenure security etc.) instead of macroeconomic land-use drivers (such as export markets) or nationwide social/cultural norms (Fisher, 2010; Kaimowitz & Angelsen, 1998). Gender roles at this scale often indirectly influence how the land is used, based on gendered labor practices and intra-household specialization (B. Agarwal, 2000, 2009; Upadhyay, Arpornsilp, & Sootornwong, 2013). Evidence from Rwanda, Kenya, Burkina Faso and Thailand suggest that women generally use forests for harvesting NTFPs, whereas men are more likely to be involved in timber production, hunting, or relatively high-yield agriculture (Ali et al., 2014; Coulibaly-Lingani et al., 2009; Dewees, 1995; Upadhyay et al., 2013). These roles are largely complimentary and are not universal, so the degree to which gendered land tenure and gender inequality might affect forest degradation and deforestation is still unclear. Correlating spatially explicit land-based indices of gender inequality with land cover change, however, could highlight a potential relationship while considering the high degree of variability of gender relations and forest use.

Measures of Gender Inequality

The implications of worldwide gender inequality for economic, cultural, and environmental issues are important to understand in order to come up with comprehensive and equitable policies that address underlying causality. Gender inequality is increasingly seen as a vital dimension, as it is commonly associated with other dimensions of inequality and barriers to human well-being (Deda & Rubian, 2004; *The Rio Declaration*, 1992). Measuring global gender inequality is an important step in identifying ways to improve gender issues (Crawford, 2012; Dijkstra & Hanmer, 2000; Upadhyay et al., 2013). Differing indices and indicators for gender inequality come from a variety of disciplines, such as psychology, economics, education, sociology, and anthropology (Charmichael & Rijpma, 2017; Glick et al., 2004; Szołtysek, Klüsener, Poniat, & Gruber, 2017).

Aims to quantify gender inequality generally fall short on several fronts, however. First, there is little continuity over time in these indices, so the temporal variation in inequality is largely not documented within a single metric (Szołtysek et al., 2017). This presents difficulties in adapting historical data to current data. There are certain indices that aim to address historical changes in gender dynamics, but these typically do not take into account the same variables as the more mainstream post-1990 measures (Szołtysek et al., 2017). Another limitation of these indices is that they are often developed for use at the national scale, thus obscuring the heterogeneity of community-scale gender dynamics (Buvinic, Furst-Nichols, & Koolwal, 2014; Charmichael & Rijpma, 2017). This is problematic from a policy perspective, as policies developed for national implementation that are based off of these indices can miss certain local dynamics that produce more gender-equitable conditions and re-enforce others that lead to greater gender inequality (Yngstrom, 2010). Another shortcoming of the literature on gender inequality measurement is that these indices often aim to separate gender inequality from other dimensions of inequality (Staveren, 2013). Numerous studies have shown the inextricable relationships between gender inequity other systems of inequality, such as age discrimination and racial discrimination (Duncan & Loretto, 2004; Staveren, 2013). Additionally, many measurements assess gender inequality as a separate dimension from a country's overall level of development (usually as indicated by the Human Development Index, or HDI) (Staveren, 2013). This is problematic because it leads to index values that are aggregated by a variable that is nationally heterogeneous, thus taking a measurement that is relative to a country's HDI and comparing it in absolute terms to other countries (Szołtysek et al., 2017). Finally, these indices also fail to account for informal economic opportunities that women have and unpaid and unregulated labor that they engage in, especially with regard to the agricultural sector and household labor (Buvinic et al., 2014; Seguino, 2000). Van Staveren (2013) outlines five gender inequality indices and their characteristics. These were chosen based on their accessibility, use in reputable sources, and their application in at least 100 countries. Figure 2 is adapted from van Staveren (2013), and shows these indices along with what they measure and how they can be interpreted.

Index	Source organization	What it considers	How to interpret
Gender Equality Index (GEI)	Indices of Social Development database of the Institute of Social Studies of Erasmus, University Rotterdam	Gendered access to resources and rights, attitudinal measures, wellbeing indicators, qualitative & quantitative measures, women's economic and social rights (latter two are both composites as well)	Number lies between 0 and 1. The higher the digit the more equal gender relations for that country are
Gender Inequality Index (GII)	UNDP Human Development Reports	3 dimensions of human development with equal weights and 5 indicators of gender inequality.	Reveals the extent to which development outcomes are eroded by gender inequality. Number lies between 0 and 1, the higher the number, the more gender inequality persists in that country
Social Institutions and Gender Index (SIGI)	Based on the Gender and Institutions database from the OECD	Gendered institutions: family code, physical integrity, son preference, civil liberties, and ownership rights – Values are weighted due to nonlinearity	Values lie between 0 and 1 and the higher the number the more unequal gender relations are
Global Gender Gap Index (GGGI)	World Economic Forum	Measures gaps in development variables between men and women, expressed as female/male ratios. Covers economics, education, health, politics, and has 14 total indicators	Values lie between 0 and 1 and the higher the number the more equal gender relations are
Women's Economic and Opportunities Index (WEOI)	Economic Intelligence Unit (EIU)	Uses 26 indicators of economic development as defined by the EIU	Values lie between 1 and 100, the higher the number the more equal gender relations are

Figure 2. Quantitative measures of gender inequality. Adapted from van Staveren (2013).

While these indices are important for assessing national-level changes, they generally ignore local dynamics that are not easily changed by national policy directives (Yngstrom, 2010). These indices also mostly ignore informal rights that women have and nuances with regard to intra-household gender expectations (Fuwa, 2004). Indices that consider micro-scale gender dynamics are thus important, as they can provide insights into interactions that are obscured by national aggregation. Additionally, geographic variation is useful for identifying trends, patterns, exceptions, and areas of concern with regard to inequality (Charmichael & Rijpma, 2017). Data gaps are still extremely prevalent with respect to gender-disaggregated spatial data (Buvinic et al., 2014). One study, however, created a new spatial dataset based on coded ethnographic research to map familial constraints on women (FCOW) at the scale of ethnic group (Charmichael & Rijpma, 2017). They then created a model to identify geographic factors that correlate with their index (Charmichael & Rijpma, 2017). This revealed correlative relationships between the FCOW for an ethnic group and distance to coast, the "ruggedness" of a society, and distance to the nearest center of agricultural revolution (with the logic being that women became less equal with the inclusion of agriculture into a society) (Charmichael & Rijpma, 2017). This method is useful for identifying geographic factors that might influence gender inequality in ethnic groups, but due to their statistical methods it is difficult to assess to what degree each has causative influence on their inequality index (Charmichael & Rijpma, 2017). Their method provides an interesting framework for understanding heterogeneity in gender inequality but does not go further in identifying how their index values might influence other localized physical features such as sources of water, biodiversity, or land cover (Charmichael & Rijpma, 2017). Using gender inequality as an independent variable is thus important as well, as this can improve our understanding of how the condition of women can affect other aspects of society that are generally considered external to gender issues. Despite numerous studies doing this with wealth inequality, there are essentially none that do the same with gender inequality at a sub-national scale (Buvinic et al., 2014).

There is considerable room for improvement of data availability when it comes to measures of gender inequality (Buvinic et al., 2014). Percentage of female parliament members is often used as a proxy for the participation dimension of inequality indices, but there are also important local institutions that are largely unaccounted for with regard to measures female participation (B. Agarwal, 2010; Dijkstra & Hanmer, 2000; Szołtysek et al., 2017). Of particular relevance to this paper is the lack of global gender-disaggregated spatial data about participation rates in local resource management groups, such as community-based forestry (CBF) and resource management (CBRM) (B. Agarwal, 2000; Upadhyay et al., 2013). Additionally, with literacy rates and school enrollment being the primary proxy measures for education, there is a gap in understanding of how informal knowledge is accessed (and used) by women, and what role this kind of knowledge plays in improving their lives in local contexts (Buvinic et al., 2014; Dijkstra & Hanmer, 2000).

Inequality and Biodiversity/Habitat Loss

There is no established systematic theory of inequality, only indices that quantify certain dimensions of it (Díaz-Giménez, Quadrini, & Ríos-Rull, 1997). Because of this, relating different dimensions of inequality to biodiversity and habitat loss demands a wide range of methodologies and considerations (Bamberger, Rao, & Woolcock, 2010). Díaz-Giménez et al. (1997) identify many different dimensions of inequality including earnings, wealth, income, age, employment status, education, marital status, ability, bequests, and tastes (identifying gender inequality involves disaggregating these by gender). The varying importance of these dimensions over space and time make them particularly difficult to assess with relation to other socioeconomic factors (Díaz-Giménez et al., 1997). For example, in sub-Saharan Africa, it may make little sense to use financial capital as an indicator of well-being, as opposed to land held for agriculture or access to improved water sources (Abdallah, Wheatley, & Quick, 2017; Díaz-Giménez et al., 1997; Fisher & Naidoo, 2016). Given the heterogeneity of community demands for resources, (especially in communities that rely on local resources and are not active in globalized markets), inequality should sometimes be assessed based on locally or contextually relevant variables as opposed to universal measures of wealth, such as income (Abdallah et al., 2017; Bamberger et al., 2010).

There is a well-documented statistically significant relationship between measures of wealth inequality (using the GINI coefficient) and biodiversity loss (Mikkelson, Gonzalez, & Peterson, 2007). Notably, there is a strong correlation between GINI coefficient and number of threatened species at a national level in 45 countries (Mikkelson et al., 2007). This suggests that paying attention to wealth and income distribution may play a role in conservation efforts (Soaga, Adegbenjo, & Oladejo, 2014). The drivers of this macroscopic relationship are diverse regarding the extent that they are rooted in international, national, or sub-national social and economic conditions (Fisher, 2010; Geist & Lambin, 2001; Rudel, 2013). Unlike economic activities such as agriculture which have easily identifiable impacts on land cover change, it is difficult to find causal relationships between dimensions of inequality and biodiversity loss because inequality is generally a composite measure with a variety of input factors (e.g. political corruption, path dependencies of inequality, historical precedent, technological changes, etc.) (Abdallah et al., 2017; Díaz-Giménez et al., 1997). The effects of economic inequality can also incorporate feedback loops and perpetuate, for example when an increase in poverty induces an increase in timber harvesting which then exceeds sustainable yield, thus exacerbating poverty for people that rely on the forest for economic productivity (Gibson, 2018). Additionally, wealth and income inequality correlate to certain gendered microeconomic issues as well (Fuwa, 2004; Seguino, 2000). Notably, women are more likely to be responsible for the production of price-elastic goods, which makes them more susceptible to the effects of price shocks (Seguino, 2000). This also affects women's ability to access financial institutions and long-term investment opportunities by restricting their ability to gain credit (Seguino, 2000). The literature on the complex relationships between economic and gender inequality indicates that these issues should be further incorporated into research about biodiversity loss, as they could precipitate or indicate land use and land cover changes in certain cases.

While economic dimensions of inequality are by far the most studied dimensions of inequality (especially in relation to habitat loss and conservation goals), there are other quantitative measures that could be useful for identifying gendered inequalities (Geist & Lambin, 2001; Mikkelson et al., 2007; Seguino, 2000). Fisher and Naidoo (2016) took an approach that quantified the inequality between male- and female-headed households as it relates to agency over land at a village scale. Mapping this at a fine scale allows for identifying spatial patterns, which may offer insights into the diversity of *de jure* land tenure practices. Fisher and Naidoo (2016) have done this with relation to gender, but there are also other variables worth considering, such as ethnic group, age, education level, etc. These kinds of correlative studies are important as a basis for deeper qualitative investigations, and for the statistical modeling of underlying drivers of global environmental change and degradation.

Hypotheses

Given the connections between gender roles and land management identified in the literature, I seek to understand:

1. Where and how do deforestation and gender inequality intersect, and how has this changed over time and space?
2. What socioeconomic and environmental variables are associated with deforestation at the cluster scale and is gender inequality in land tenure associated with deforestation?
3. How is gender inequality distributed over space in Nepal and how has this changed over time?
4. What does this mean for achieving the SDGs and implementing REDD+?

In investigating these questions, I will use correlative statistics and mapping, and interpret the according to the literature on gender, forestry, and deforestation in Nepal. Regarding the above questions, my hypotheses are as follows:

1. I expect a great deal of overall heterogeneity in the intersection of deforestation and gender inequality. However, I expect deforestation to be more prevalent in the Nepali lowlands.
2. Given the tendency of female land-holders to favor security-ensuring activities over income generation, I expect that as women control a greater share of agricultural land in a cluster, deforestation will tend to decrease, all else being equal.
3. I do not expect any significant changes over time and space in gender inequality as it pertains to my land inequality metric.

Methods

Modeling the relationship between deforestation and gender inequality

I use survey results from the Demographic and Health Surveys (DHS) from 2006 and 2011 (*Demographic and Health Surveys*, 2006; *Demographic and Health Surveys*, 2011) to calculate disparities between male and female headed households (Fisher & Naidoo, 2016; Agarwal, 2009). These surveys are conducted in over 50 countries worldwide and use 2-stage stratified cluster sampling to generate nationally-representative probability samples for each country. In this process, small geographic areas of approximately equal populations (clusters) are first chosen by a national office to be as nationally representative as possible (based on census data). Then field crews randomly sample households within each cluster. Data for each household is associated with a single longitude/latitude pair that serves as an approximate location for the cluster, displaced by up to 5 km to protect respondent anonymity. I computed the gender inequality index for each cluster as:

$$inequality_c = \mu_{male} - \mu_{female}$$

Where μ_{male} and μ_{female} are the mean amount of a household-level variable of interest for male headed and female headed households, respectively. This is generalizable to any household-level continuous variable. This also gives more weight to clusters where the difference between genders is greater relative to other clusters, as opposed to within the cluster. By doing this instead of using a ratio or a normalized index, we can see the magnitude of the gender disparity on a scale that encompasses the range of inequality present in the samples. This also lets us see whether the disparity in the cluster leans towards male or female headed households.

I use two dimensions of gender inequality as independent variables in this analysis – land available for agriculture and the DHS wealth index (a 5-digit index encompassing country-specific indicators of material wealth). These were also used by Fisher and Naidoo (2016), who mapped gender inequality as a ratio of the cluster level mean of these two variables (2016). In this analysis, they compared the average amount of agricultural land held by male-headed versus female-headed households, along with the average DHS wealth index for these two groups, for each cluster (Fisher & Naidoo, 2016). I use the amount of agricultural land that a household owns because it is one of the most important factors of household production in the developing world (Jayne et al., 2003). Because rural Nepali communities rely so heavily on forest products to support agriculture, I assume that there is some linear mapping between forest cover and agricultural land stewardship (Bajracharya, 1983; Basnet, Oli, & Dhungana, 2018; K. Bhattarai, Conway, & Yousef, 2009; Reddy et al., 2018). The relationship between forests and agriculture is more complex and is likely dependent on the *type* of agriculture that dominates the cluster.

I then spatially join the DHS variables (and other independent variables, see Appendix table 1) to deforestation data from Hansen et al. (2013). This data is derived from Landsat 7 and 8 imagery and documents yearly forest loss and gain around the world at a 30M resolution (Hansen et al., 2013). To account for the 5 km geographic offset of the DHS data, I computed the area within a 5 km buffer around the clusters that was deforested either two years prior to the survey, the year of the survey, or two years after the survey.

I then use regression analysis to estimate the impact of the inequality metrics on deforestation for Nepal in 2011 (D. K. Agarwal, Silander, Gelfand, Dewar, & Mickelson, 2005). My dependent variable in each regression model is the deforestation variable described above (Hansen et al., 2013). Following exploratory analysis, I use three methods for computing linear regression models: Manual variable selection based on known proximate drivers of land cover change as outlined in Geist and Lambin (2001), bidirectional stepwise regression, and least absolute shrinkage and selection operator (LASSO) regression. Bidirectional stepwise regression is a method of variable selection that tests whether incorporating each variable makes the whole model “better”. In this case, I used Akaike’s Information Criterion to select a “best” model, as is often used in variable selection.

LASSO Regression is a form of regularized regression and variable selection that seeks to solve the constrained optimization problem:

$$\beta^{LASSO} = min \left\{ RSS + \lambda \sum_{j=1}^{p} |\beta_j| \right\}$$

Where β^{LASSO} is the vector of model coefficients, RSS is the residual sum of squares, p is a predictor in the model, and $\lambda \sum_{j=1}^{p} |\beta_j|$ is the shrinkage penalty on the model (the L1 Norm). The L1 Norm shrinks coefficient estimates towards zero as λ increases, creating a constraint space relative to the minimum of the RSS. λ can be thought of as a hyperparameter that tells us how we should balance the model's bias with its variance. In other words, LASSO minimizes the residual sum of squares *subject to* the L1 Norm. The square geometry of the L1 Norm constraint space allows for coefficients to be set to 0, thus eliminating some predictors from the "best" model (chosen via cross-validation) (see Appendix figure 1).

Mapping gender inequality over time

The DHS uses two level stratified cluster sampling for each year, meaning that household clusters are selected first, followed by a random sampling of those households within the cluster (*Demographic and Health Surveys*, 2006; *Demographic and Health Surveys*, 2011). This leads to different geographic areas being sampled for each survey, causing incommensurability between clusters over time. To account for this, I create an interpolated prediction surface for each sample year using Empirical Bayesian Kriging (EBK). EBK is a method of interpolation that, unlike traditional kriging methods, accounts for the error in the underlying semi variograms through a process of sub setting and simulation, creating many semi variograms for a given dataset based on the distributions generated (Krivoruchko, 2012). It uses the distribution of semi variograms to estimate parameters for the kriging model, eliminating the need for hyperparameter tuning on the user side. After using EBK to generate prediction surfaces for both sample years, I subtract the 2011 surface from the 2006 surface to create a new surface showing the change between 2006 and 2011. Due to a previous method I used in the research process, these surfaces reflect the absolute disparity between male and female-headed households, but not which direction the disparity is in.

Characterizing clusters based on inequality and deforestation

Using the metrics of inequality and deforestation that I generated for my model, I classify each cluster into one of four quadrants:

- *Low deforestation, female slanted* (LDFS): Clusters with below the median log-transformed deforestation rate and, on average, more land controlled by female-headed households than male-headed households

- *Low deforestation, male slanted* (LDMS): Clusters with below the median log-transformed deforestation rate and, on average, more land controlled by male-headed households than female-headed households
- *High deforestation, female slanted* (HDFS): Clusters with above the median log-transformed deforestation rate and, on average, more land controlled by female-headed households than male-headed households
- *High deforestation, male slanted* (HDMS): Clusters with above the median log-transformed deforestation rate and, on average, more land controlled by male-headed households than female-headed households

Using this bivariate classification scheme, I then map out clusters for each year, as Rasolofoson did with watersheds in Kenya (2019, in preprint).

Results

Summarizing the DHS data

The variables central to hypothesis 1 are highly variable. Table 1 shows summary statistics for each gender specific variable, along with the computed inequality indices and deforestation rates for clusters of both survey years. Both the inequality metrics and deforestation rates are log-normally distributed. Extremely high values reflect the heterogeneity in gender inequality at the community scale. Additionally, these distributions exist for both sample years.

	2006 (n=260)				**2011 (n=232)**			
Variable	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Male land (mean hectares/hh)	0.719	1.267	0	11.96	1.189	2.849	0	29.94
Female land (mean hectares/hh)	0.793	2.928	0	33	0.679	1.896	0	25.38
Male wealth (mean wealth index/hh)	5,432	88,370.71	-90,549	286,593	4,120	87,466.32	-90,549	272,036
Female wealth (mean wealth index/hh)	2,853	93,606.7	-93,287	293,428	1,528	92,885.07	-93,287	293,428
Land inequality	9.08	71.54	0	1069.84	11.77	76.70	0	837.69
Wealth inequality	7.51×10^8	2.24×10^9	2.75×10^4	2.49×10^{10}	7.14×10^8	2.24×10^9	2.8×10^4	2.49×10^{10}
Deforestation (M^2 within 5km buffer)	70,456	156,095	0	1,840,461	96,881	239,522	0	2,927,603

Table 1. Summary statistics for DHS and deforestation data for 2006 and 2011 sample clusters. High variance in inequality and deforestation rates reflects the community-scale heterogeneity in these variables.

Characterizing clusters based on inequality and deforestation

Deforestation rates and gender inequality for agricultural land are mapped in figures 3 and 4, respectively. The overall distribution of the intersection between cluster deforestation and gender inequality for agricultural land ownership is given in figure 4. This is mapped in the corresponding figure 5.

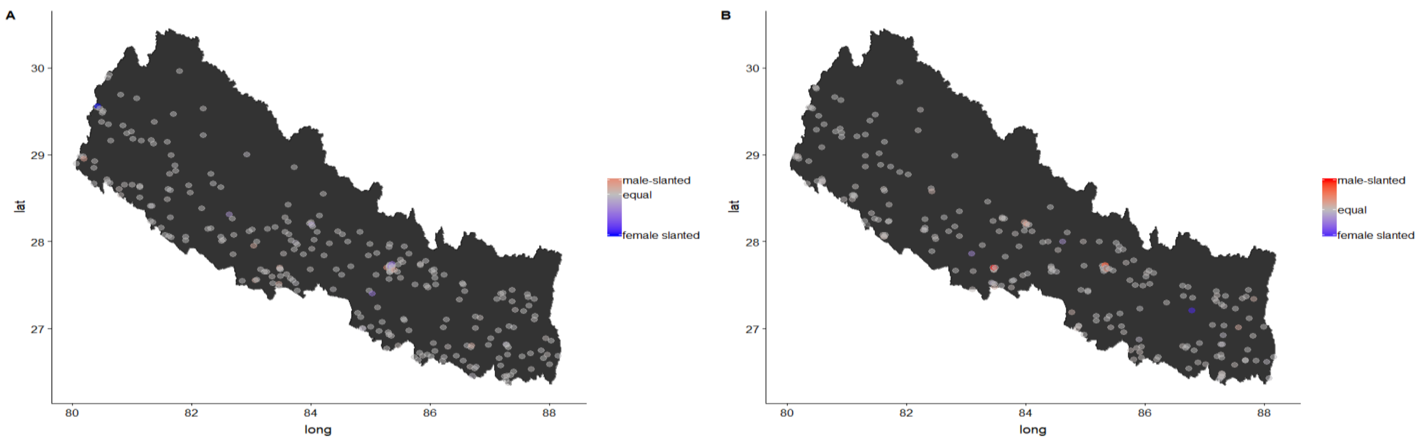

Figure 3. Map of gender inequality of agricultural land ownership for 2006 (A) and 2011 (B). Note that most clusters are centered around the mean. Implemented using `R`'s `ggplot2`.

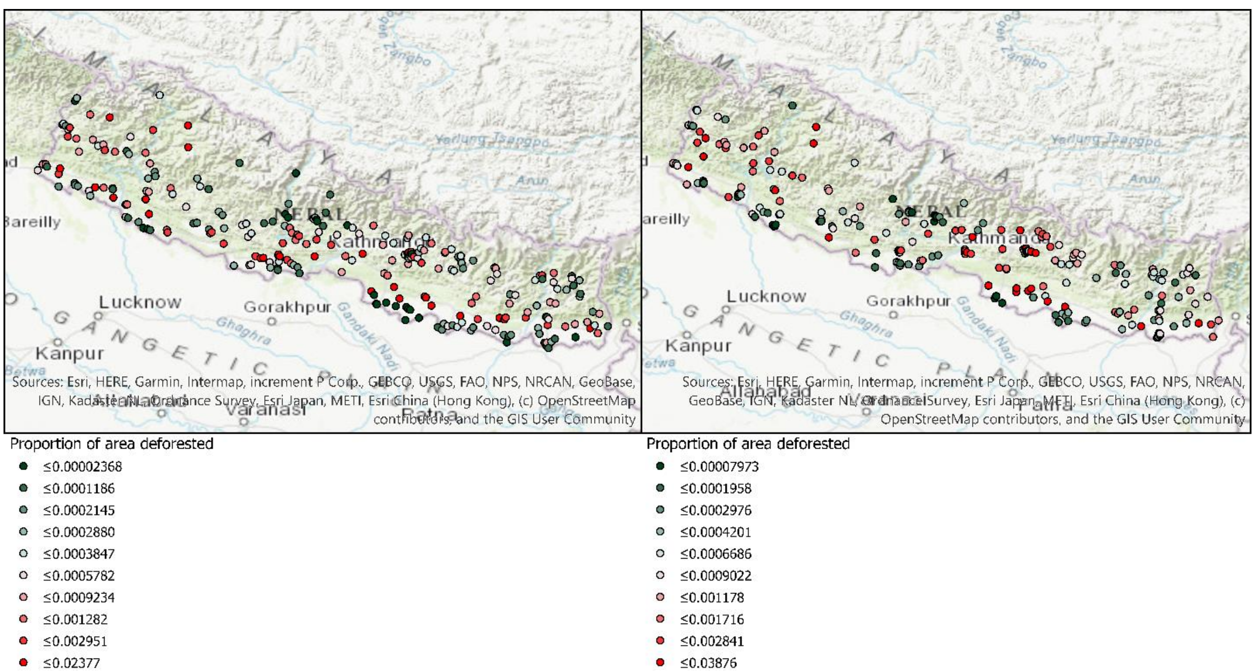

Figure 4. Map of deforestation rates for 2006 (left) and 2011 (right). The proportion being displayed is simply the area deforested in a cluster buffer divided by the amount of land in the buffer, which is constant. Implemented using ArcGIS Pro.

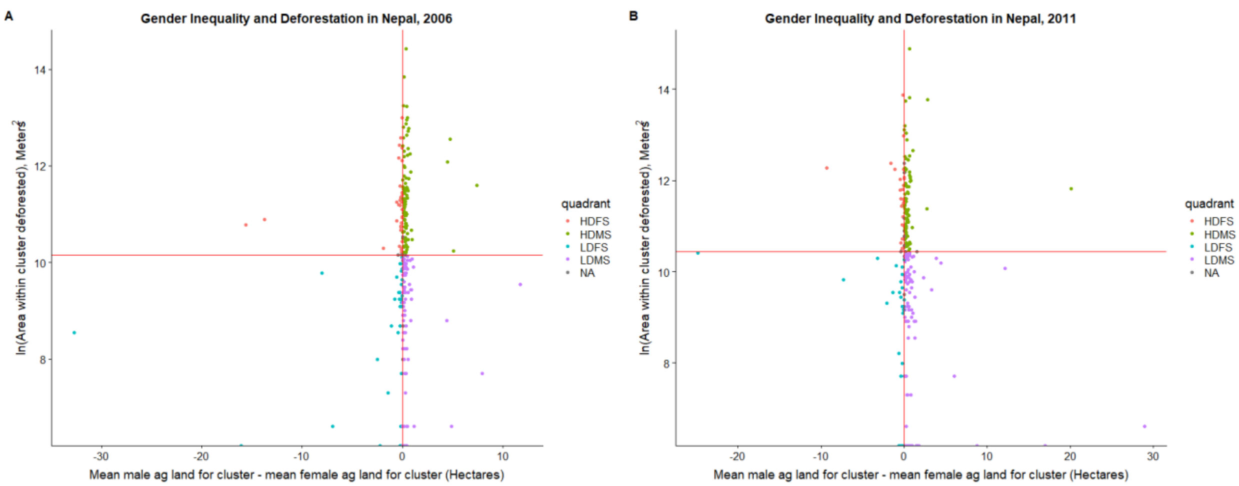

Figure 5. Distribution of deforestation rates and gender inequality of agricultural land ownership for 2006 (A) and 2011 (B). Quadrants are divided up by the median of each variable, for each year. NA values come from variables located on the boundaries between quadrants. Acronyms of each quadrant given on page 20. Implemented using `R`'s `ggplot2`.

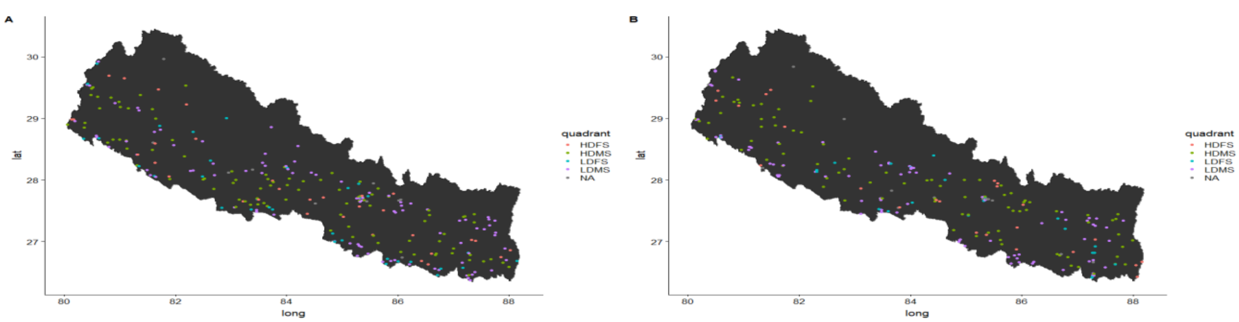

Figure 6. Spatial distribution of deforestation rates and gender inequality of agricultural land ownership for 2006 (A) and 2011 (B). Colors correspond to legend in figure 2. Implemented using `R`'s `ggplot2`.

Changes in gender inequality over time

DHS sample clusters are randomly chosen across the country. Sample sites are given in figure 7 for both 2006 and 2011. There is spatially invariant sampling in the Nepali lowlands over time, but sampling in the Northern mountainous regions was sparse. The extent of the prediction and error surfaces generated by EBK reflects this, as the layer is bounded in the Northern, mountainous parts of the country where there were fewer clusters (see figure 8). Additionally, values of inequality used for EBK were squared, so while the interpolated surface does not show whether areas are inequal towards men or women, it is still proportional to the disparity between genders over time.

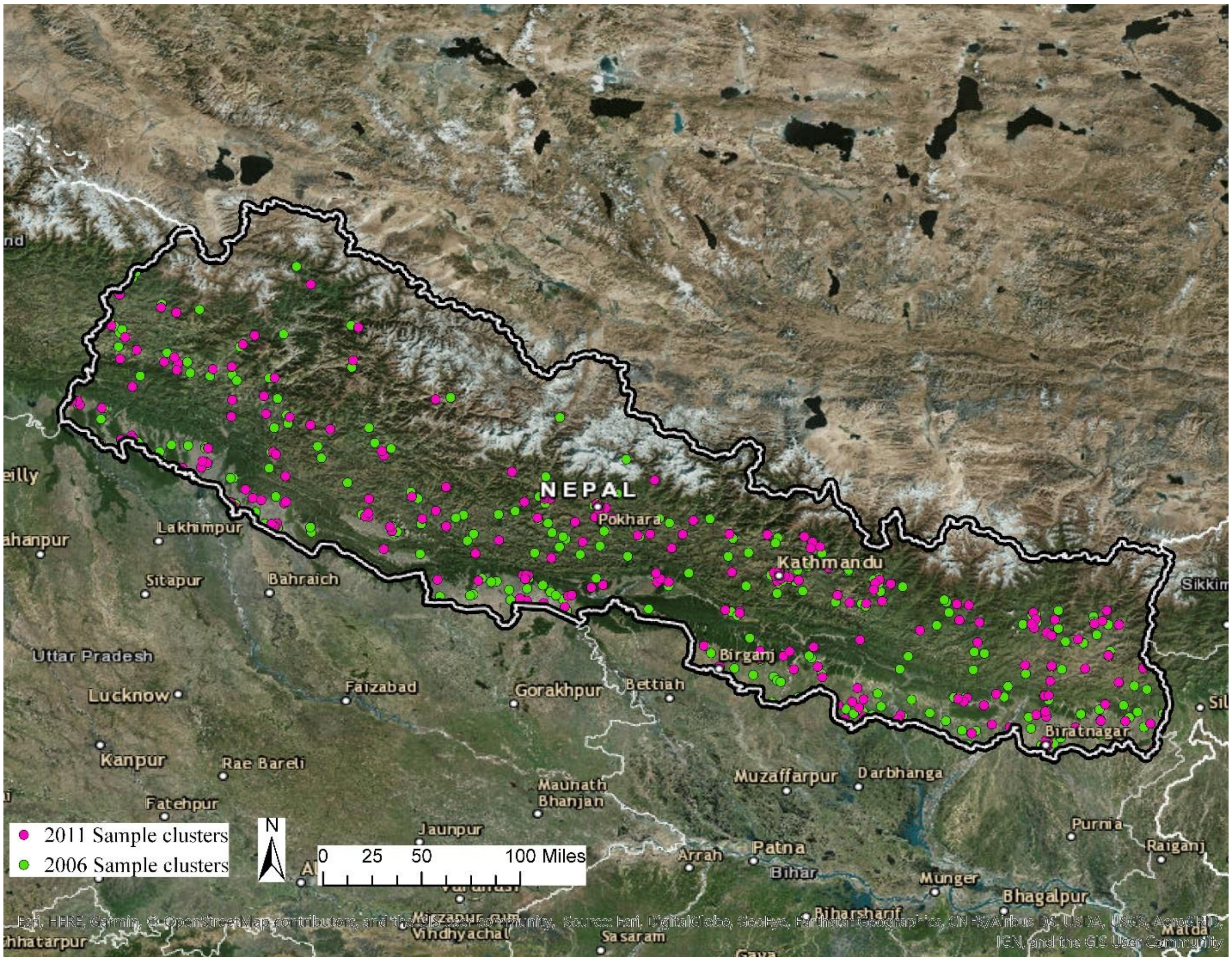

Figure 7. DHS sample locations for Nepal in 2006 and 2011. The DHS uses a cluster-sampling strategy in which a group of households are selected (a cluster), and within the cluster, another group of households is randomly surveyed (*Demographic and Health Surveys*, 2006; *Demographic and Health Surveys*, 2011). For 2006, 8,707 households were surveyed across 260 clusters. For 2011, 10,826 households were surveyed across 232 clusters.

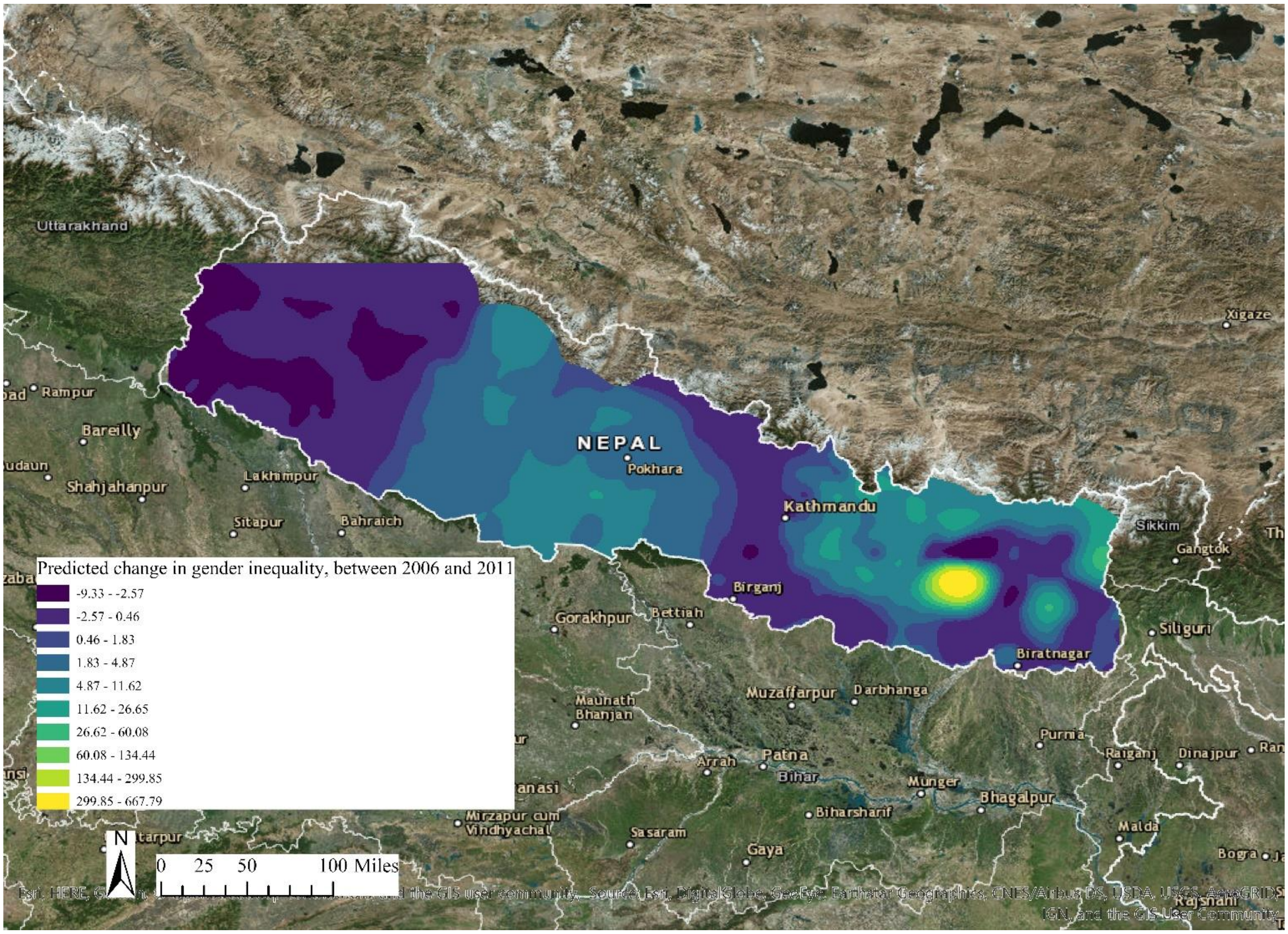

Figure 8. Prediction surface for the changes in gender inequality over space as it pertains to agricultural land ownership between 2006 and 2011. Negative values indicate that gender inequality decreased over time, positive values indicate that it increased. Generated using Empirical Bayesian Kriging, an interpolation method that uses Monte Carlo methods and leave-one-out cross validation to sample from the empirical semi variogram of the data, creating a modeled prediction surface (Krivoruchko, 2012). Implemented using ArcGIS Pro.

Incorporating gender inequality into linear regression models

Before running these models, I subset the whole data to only include rural clusters, given that agricultural land is primarily a meaningful indicator of household wellbeing only in rural areas where access to markets tends to be more limited (Jayne et al., 2003). I then created histograms and a correlation matrix for the whole dataset to explore the distributions and bivariate relationships present in the data (see figures 9 and 10, respectively. See Appendix table 1 for description and source of each independent variable).

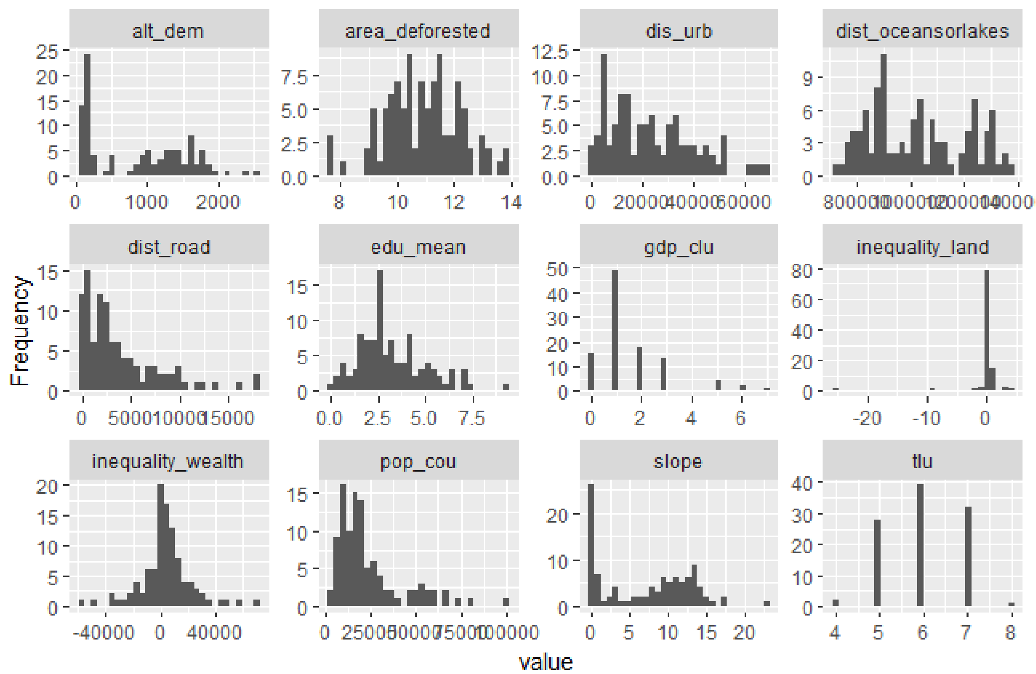

Figure 9. Histograms for DHS and deforestation data along with independent variables used for modeling. Note that certain variables (gdp of the cluster, ruminant livestock density (tlu)) are estimated at a fairly coarse spatial resolution, so their distributions are sparse. See Appendix table 1 for description and source of each variable.

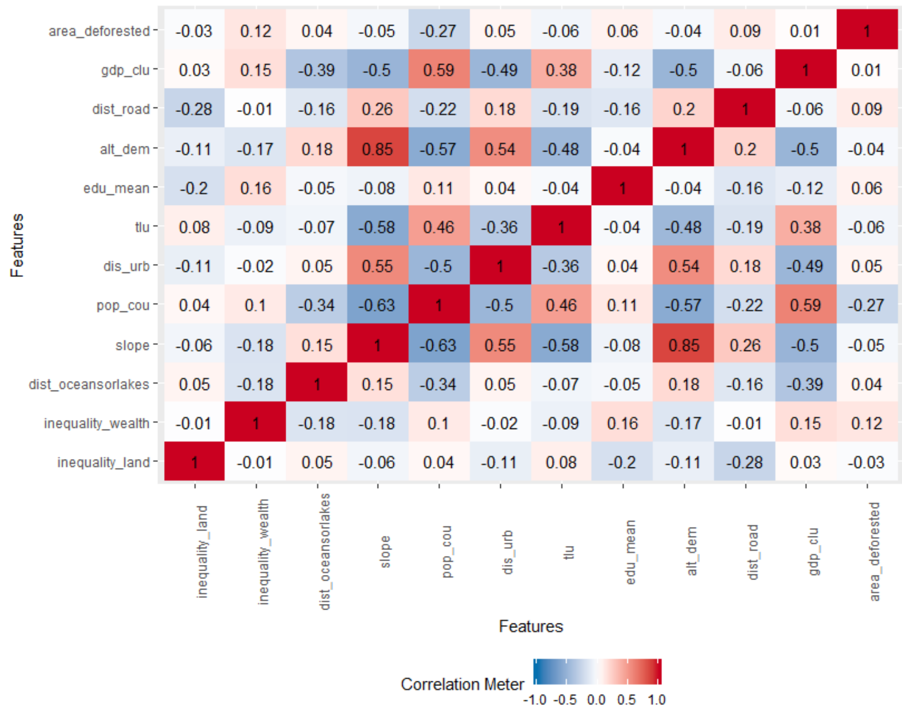

Figure 10. Bivariate correlation matrix for all features in dataset. Intensity of color indicates strength of linear relationship. Color indicates negative or positive correlation between variables. See Appendix table 1 for description and source of each variable.

In the manually generated model, cluster GDP was significant at the 0.1 level for explaining the variation in deforestation within the whole model. Additionally, population was the strongest predictor, being strongly negatively associated with deforestation rate, whereas GDP is positively associated to it. The whole model was also significant (Adjusted R^2 = 0.11, p = 0.03).

Predictor	*b*	*b* 95% CI [LL, UL]	*beta*	*beta* 95% CI [LL, UL]	sr^2	sr^2 95% CI [LL, UL]	*r*
(Intercept)	11.98***	[8.32, 15.65]					
inequality_land	0.00	[-0.09, 0.09]	0.00	[-0.19, 0.20]	.00	[-.00, .00]	-.03
inequality_wealth	0.00	[-0.00, 0.00]	0.06	[-0.15, 0.26]	.00	[-.02, .02]	.12
Distance to oceans or lakes (M)	0.00	[-0.00, 0.00]	0.00	[-0.22, 0.22]	.00	[-.00, .00]	.04
Mean cluster slope (degrees)	-0.07	[-0.16, 0.02]	-0.32	[-0.73, 0.08]	.02	[-.03, .07]	-.05
Population within 5km buffer (people)	-0.00***	[-0.00, -0.00]	-0.59	[-0.88, -0.31]	.16	[.03, .28]	-.27***
Distance to nearest urban area (M)	0.00	[-0.00, 0.00]	0.04	[-0.21, 0.28]	.00	[-.01, .01]	.05
Ruminant livestock density at 10km grid, circa 2000 (tropical livestock units)	-0.08	[-0.46, 0.29]	-0.05	[-0.30, 0.19]	.00	[-.01, .02]	-.06
Mean education years of household head	0.09	[-0.06, 0.23]	0.12	[-0.09, 0.32]	.01	[-.03, .05]	.06
Altitude of cluster (M)	-0.00	[-0.00, 0.00]	-0.04	[-0.40, 0.32]	.00	[-.01, .01]	-.04
Log(Distance to nearest road) (M)	0.04	[-0.15, 0.23]	0.04	[-0.16, 0.24]	.00	[-.01, .02]	.05
GDP of cluster at 30km grid (USD)	0.21	[-0.04, 0.46]	0.23	[-0.04, 0.49]	.03	[-.03, .08]	.01*

Table 2. Regression results using log(Deforestation) as the criterion. Manual variable selection method. R^2 = .242***.* A significant *b*-weight indicates the beta-weight and semi-partial correlation are also significant. *b* represents unstandardized regression weights. *beta* indicates the standardized regression weights. sr^2 represents the semi-partial correlation squared. *r* represents the zero-order correlation. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively. Implemented in statistical package R.
* indicates *p* < .1. ** indicates *p* < .05. *** indicates *p* < .01.

Results from lasso and stepwise regression indicate that none of the gender inequality metrics I present are linearly associated with deforestation. Stepwise regression yielded a best model that includes population density, GDP, and mean cluster slope as predictors. According to this model, slope (p < 0.05) and population (p < 0.001) are negatively associated with deforestation, whereas GDP (P < 0.1) is positively associated with it (see table 3). Lasso regression yielded a result in which the cross-validated model set the coefficients to 0 for all variables except population (See Appendix plots 1-2 for LASSO trace plots).

Predictor	*b*	*b* 95% CI [LL, UL]	*beta*	*beta* 95% CI [LL, UL]	sr^2	sr^2 95% CI [LL, UL]	*r*
(Intercept)	12.14***	[11.35, 12.92]					
Mean cluster slope (degrees)	-0.07***	[-0.13, -0.02]	-0.33	[-0.57, -0.09]	.06	[-.02, .15]	-.05**
Population within 5km buffer (people)	-0.00***	[-0.00, -0.00]	-0.59	[-0.84, -0.33]	.17	[.04, .31]	-.27***
GDP of cluster at 30km grid (USD)	0.18	[-0.03, 0.39]	0.19	[-0.04, 0.42]	.02	[-.03, .08]	.01*

Table 3. Regression results using log(Deforestation) as the criterion. Bidirectional stepwise regression method. R^2 = .153***. A significant *b*-weight indicates the beta-weight and semi-partial correlation are also significant. *b* represents unstandardized regression weights. *beta* indicates the standardized regression weights. sr^2 represents the semi-partial correlation squared. *r* represents the zero-order correlation. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively. Best model chosen through Akaike's Information Criteria, implemented using `R`'s `MASS` package, specifically the `stepAIC` function.
* indicates $p < 0.1$. ** indicates $p < .05$. *** indicates $p < .001$.

Predictor	Estimate
(Intercept)	11.09
Population within 5km buffer (people)	$-7.16*10^{-6}$

Table 4. LASSO regression results using log(Deforestation) as the criterion. Cross validation yielded a model where λ = 0.2. Implemented with the `cv.glmnet` function from `R`'s `glmnet` package. See appendix figures 1-2 for trace plots of the L1 Norm relative to the coefficients and values of λ relative to the mean square error of the model.

Discussion

Characterizing clusters based on inequality and deforestation

Across Nepal, the intersection of high deforestation and gender inequality varies greatly. Despite deforestation rates being somewhat clustered in certain pockets – especially in far Eastern Nepal and around Kathmandu - there is no obvious pattern as to how these variables intersect for either sample year, or between sample years. This highlights how national-level policies are necessary, but not enough, in meeting the goals outlined by both the SDGs and REDD+. To this end, Nepal takes a community-based approach in forest management with over one third of forest land being managed by community forestry groups (under government oversight) (Basnet et al., 2018). While this decentralized approach to forest governance is seen by many as a great strength of Nepal's implementation of REDD+, it does not address or account for gender inclusion within these localized management groups (Basnet et al., 2018; Khadka et al., 2014). Many inequalities persist at the local level despite national efforts to make forest management more equitable, highlighting a need for more localized planning (Khadka et al., 2014).

Changes in gender inequality over time

Mapping the changes in gender inequality between the two sample years using EBK yielded a prediction surface that, at first glance, seems to show a massive increase in inequality in the area surrounding Diktel, a municipality in Khotang District directly south from Mount Everest and Southwest of Kathmandu. While this could indicate a dramatic change over time for the region, it is more likely that it reflects the heterogeneity between villages across sample years. This is supported in that the 2011 sample cluster in this area has an extremely high inequality index (616.85), while the three nearby clusters from 2006 all have inequality indices that are < 1. So rather than reflecting a spike in inequality over time, the surface simply shows a disproportionate weight given to an extreme value.

By using this method, I assume that gender inequality is spatially autocorrelated to some degree (Krivoruchko, 2012). The DHS-derived inequality data does not exhibit significant spatial autocorrelation (Moran's Index of spatial autocorrelation > 0.1 for both sample years). This means that the EBK step used a highly nonlinear, probably inaccurate semi variogram to make estimates, creating a prediction surface that is more a result of mathematical hoop-jumping than any real spatial relationship between the data. The rest of this section should be interpreted with these limitations in mind.

In general, far western Nepal became more gender equal between the sample years. Central Nepal near Pokhara got slightly less equal, except for the Northernmost region in the Annapurna range of the Himalayas. This is one of the most popular hiking destinations in the world, making Pokhara the largest tourism hub in Nepal. Between 2006 and 2011, Tourism in Nepal increased by over 91% (Ghimire, 2016). Additionally, travel to Nepal specifically for holiday/pleasure increased from 27.7% of tourists in 2006 to 57.8 percent of tourists in 2011 (Ghimire, 2016). It is possible that this led to disproportionate urbanization and infrastructural development in the area, driving more urban migration from men in rural households, thus elevating the role that rural women have in managing agricultural land (Lama et al., 2017). This fits with many accepted theories of male outmigration, in that urban industries are generally more lucrative than agriculture (Lama et al., 2017; Rudel, 2013). Regions East of Kathmandu in the prediction surface are highly heterogeneous in how they changed over time.

Modelling deforestation with gendered dimensions of land tenure

Results from my linear regression models show that there is no statistically significant linear relationship between gender inequality and deforestation rates for both agricultural land inequality and wealth inequality. This in some ways supports the literature on this topic in that it shows the degree to which this relationship may vary based on social norms, microeconomic conditions, and societal attitudes towards women, all of which are not directly captured by the data I used (Desai, 1994). This fits with the overarching notion that socioecological context varies greatly in Nepal, especially regarding gender norms and practices (Morgan & Niraula, 1995).

Both my manually created model and the stepwise model include slope as a significant predictor of deforestation. The coefficient values suggest that the greater the mean slope is in the cluster buffer (in degrees), the less deforestation tends to occur there in the two years before and after the survey. The reason for this is largely infrastructural, since areas with steep slopes tend to be in remote, mountainous areas where forest clearing is extremely costly and/or dangerous. The other logical explanation for this is that clusters with steep average slopes are mostly in the Himalayas where there is little forest cover compared to the subtropical Nepali Lowlands (known as the Terai). This follows results from K. Bhattarai et al. (2009) who point out that deforestation in the Terai was rampant during Nepal's civil war from the early 1990s until the mid-2000s. They suggest that this period of civil unrest led to a lack of oversight in rural areas, leading to massive forest clearing by these communities for subsistence agriculture (K. Bhattarai et al., 2009). While the war officially ended in 2006, it is possible that this trend continued due to sociopolitical differences between the Terai and mountainous regions.

Additionally, all the models included population, which suggests deforestation rates are negatively associated with an increase in people. This is likely a characteristic of the geophysical properties of the cluster as opposed to a separate driver of deforestation. In this case, the natural log of population is colinear with slope ($\ln(\beta_{pop}) = -5.58$, $R^2 = .467$, $p = 2.497 \times 10^{-15}$), indicating the occurrence of collinearity in the stepwise model and manual models. Lasso regression penalizes coefficients proportional to their absolute values, so given a linear relationship between two variables, it will set one of them to be zero, hence why the cross-validated model left population density out. Lastly, we also see a positive association between GDP and deforestation in the manually created model. This suggests that rural clusters with higher GDP may be more likely to have higher deforestation rates. While not a very strong linear relationship, this would make sense in context, given that deforestation in Nepal is primarily driven by income-generating activities as opposed to subsistence uses (Bajracharya, 1983; K. Bhattarai et al., 2009).

There are likely confounding factors that influence the relationship between gender inequality and deforestation. Many men of nuclear families in Nepal migrate out of the home to earn income, thus making the female the *de facto* head of the house (Lama et al., 2017). This tends to increase female autonomy, but also promotes time poverty and relegates women to household activities if there is no other individual capable of doing so (Khadka et al., 2014; Lama et al., 2017). It is unclear as to whether outmigration is considered in determining household headship in the DHS, and it is certainly possible that this is dealt with heterogeneously throughout the survey. This would greatly affect the validity of this variable as a proxy for agency over household agricultural land, so the results of the modeling component of this analysis should be taken with caution. Additionally, the head of the household is not necessarily the family member that controls the access, use, and labor pertaining to the house's agricultural land (Ali et al., 2014; Goldstein et al., 2015). Given that my data do not address this intra-household nuance, my models are agnostic towards the sociodemographic and microeconomic diversity of Nepal. This is a significant limitation of my approach because of how these contexts both cause and result from gender disparities (K. Bhattarai et al., 2009).

Finally, I did not systematically search for interactions within the data, which could exist. Specifically, I would be interested to see if the dominant type of agriculture practiced in a cluster influences whether agricultural land management relates to deforestation. In Nepal, this would make sense since most forest products that go towards agriculture are specifically for animal fodder (Bajracharya, 1983; K. Bhattarai et al., 2009; Reddy et al., 2018).

Conclusions/Future work

In this paper, I bring together socioeconomic, environmental, and geophysical data to understand how gendered inequalities relate to deforestation. I mapped the intersections of deforestation rates and inequality rates in Nepal and analyzed how gender inequality may have changed over time between 2006 and 2011. While far from conclusive in any sense, this paper points towards areas of future research that will be critical for inclusively engaging in sustainable ecosystem management. Promoting the creation of gender-disaggregated socioeconomic data, analyzing smallholder decision-making regarding land use, and leveraging qualitative data are all ways in which researchers should engage with this topic further. Additionally, the limitations of this paper highlight a need for geolocated *panel* datasets combining environmental, sociocultural, and economic variables. While this is out of bounds for the DHS framework given the sensitivity of the data they collect, international conservation and development agencies should seek ways in which this could be accomplished efficiently through other means. Recent advances in remote sensing technologies, open source software, and computational linguistics represent opportunities to further merge environmental and sociocultural data, especially in rural and poor regions of the world. Using these tools will be critical for development and conservation agencies to learn more about the communities, environments, and economies they seek to assist.

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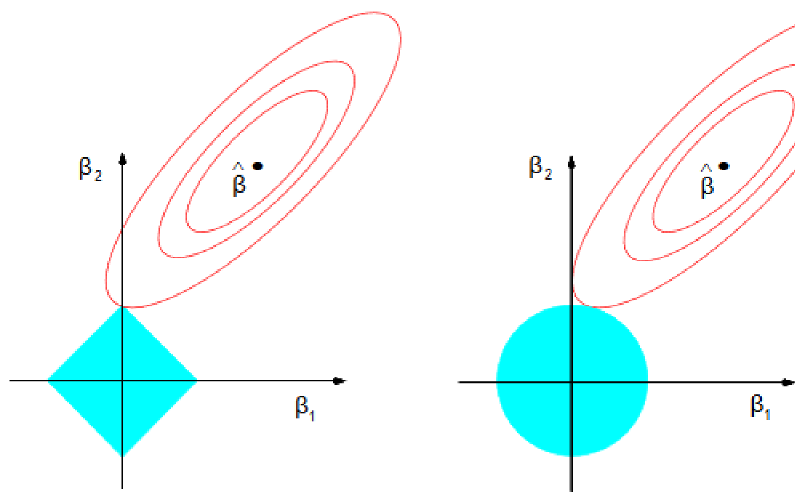
Appendix

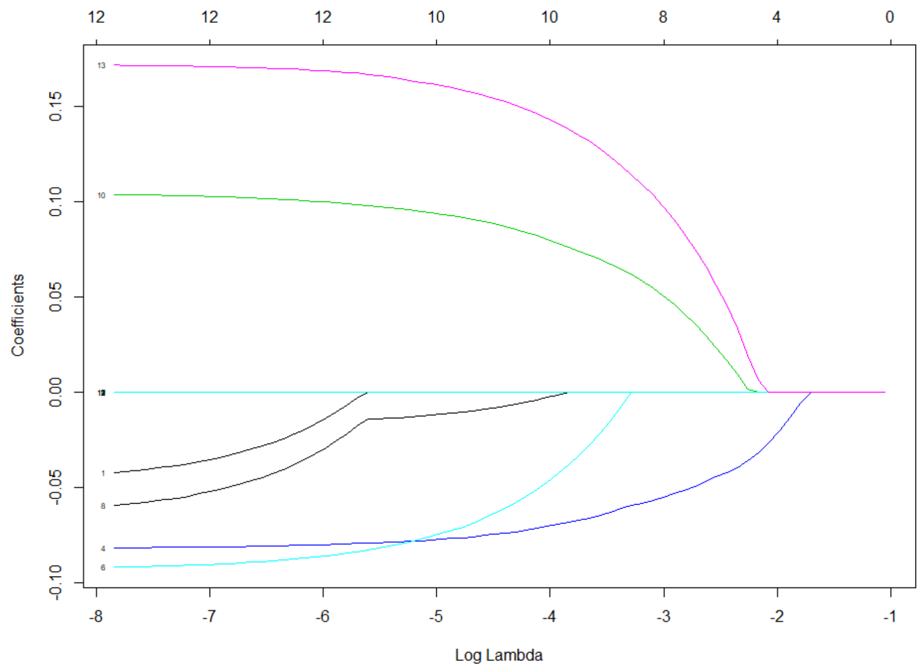
Variable	Unit	Source & description
Mean cluster slope (slope)	Degrees	Jarvis, A. et al. 2008. Hole-filled SRTM for the globe Version 4. Available at: http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1 Remotely sensed data. Derived from NASA's Shuttle Radar Topographic Mission (SRTM). Provides DEM mosaic for whole world, from which slope was derived.
Population within 5km buffer (pop_cou)	people	Center for International Earth Science Information Network - CIESIN - Columbia University. 2016. Gridded Population of the World, Version 4 (GPWv4): Population Count Adjusted to Match 2015 Revision of UN WPP Country Totals. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). http://dx.doi.org/10.7927/H4SF2T42. Accessed 1/19/2017. Gridded population predictions based on country-level data. Based on 1990 USD. Used by UN, IPCC for economic projections, based on SRES2 scenario. See link for more information on methodology.
Distance to nearest urban area (dist_urb)	Meters	Millennium Ecosystem Assessment. 2005. Millennium Ecosystem Assessment: MA Population. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). http://dx.doi.org/10.7927/H4CF9N1K. Accessed 1/18/2017 Geographic data used for the Millennium Ecosystem Assessment (2005).
Ruminant livestock density at 10km grid (tlu)	Estimated tropical livestock units	FAO/IIASA, 2010. Global Agro-ecological Zones (GAEZ v3.0). FAO, Rome, Italy and IIASA, Laxenburg, Austria. http://gaez.fao.org/Main.html#. Accessed 02/01/2017 Calculated by FAO at 10km grid for whole world. Model documented here: http://pure.iiasa.ac.at/id/eprint/13290/1/GAEZ_Model_Documentation.pdf
Distance to nearest road (dist_road)	Meters	De Sherbinen, Alex. Socioeconomic Data and Applications Center - Columbia University. 2013 http://www.ciesin.columbia.edu/confluence/display/roads/Global+Roads+Data;jsessionid=13A008A7F778CD92D57E6861E3D59D80
GDP of cluster (gdp_clu)	Estimated millions of USD at 30 km grid	Center for International Earth Science Information Network (CIESIN), 2002. *Country-level Population and Downscaled Projections based on the B2 Scenario, 1990-2100,* [digital version]. Palisades, NY: CIESIN, Columbia University. Available at http://www.ciesin.columbia.edu/datasets/downscaled Gridded GDP predictions based on country-level data. Based on 1990 USD. Used by UN, IPCC for economic projections, based on SRES2 scenario. See link for more information on methodology.
Mean education years of household head in cluster (edu_mean)	years	Demographic and Health Surveys.
Altitude of cluster (alt_dem)	Meters	Demographic and Health Surveys.

		The cluster's elevation/altitude (in meters) from the SRTM (Shuttle Radar Topography Mission) DEM (Digital Elevation Model) for the specified coordinate location.
Deforestation (area_deforested)	$Meters^2$	Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., . . . Townshend, J. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *342*(6160), 850-853. doi:10.1126/science.1244693 %J Science Area within 5 km buffer of cluster coordinates that experienced deforestation 2 years prior, during, or 2 years after survey year. Raw data is thematic raster. Area was tabulated within each buffer using ArcGIS Pro.

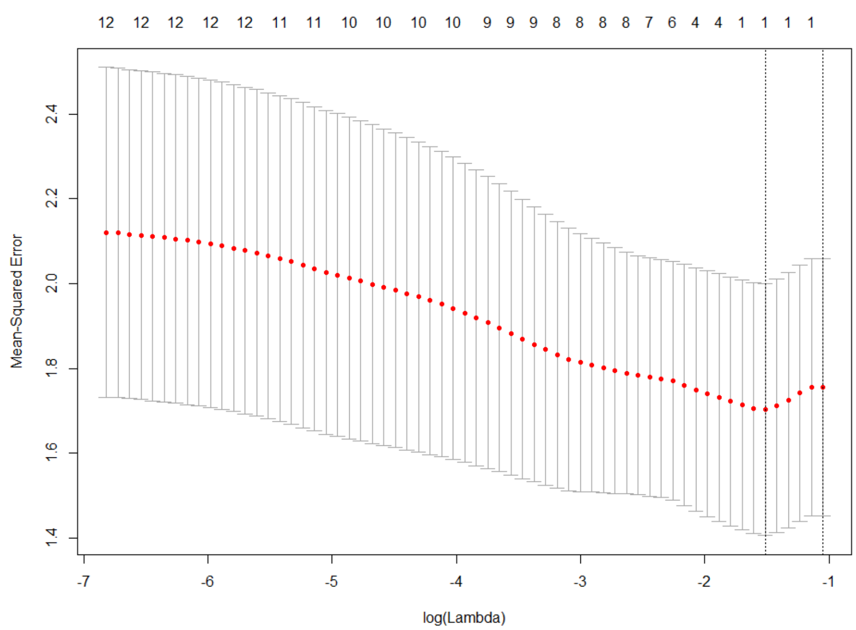
Appendix table 1. Source and description of all variables in my model for 2011. Data was compiled by team of post-docs, PhD students, and researchers over several years and passed along to me last summer.



Appendix figure 1. Graphical representation of two forms of regularized regression, from Hastie, Tibshirani, and Friedman (2009). The left, LASSO regression, is the strategy that I used. On the right is Ridge regression, which uses the L2 Norm, thus not setting any coefficients to 0. This is illustrated in the diagram where the contours are the error function (centered on the maximum likelihood estimation of the coeficcients) and solid blue areas are the constraint space. Notice how the error minima of the L1 Norm (left) intersects the constraint space where $\beta_1 = 0$. This is not possible with the L2 Norm.



Appendix figure 2. Trace plot of log λ versus standardized coefficient values for LASSO regression model. Each line represents the coefficient of an independent variable as λ increases. Higher λ values penalize model bias, thus increasing overall error. Implemented using `R`'s `glmnet` package.



Appendix figure 3. Cross validation plot of log λ versus mean square error for LASSO regression model. 95% confidence intervals are indicated by grey bars for each λ value tested.