Networks and Institutions in Sustainable Forest Use

Evidence from South-East Tanzania

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Document Version
Accepted author manuscript

Published in:
Social Networks

DOI:
10.1016/j.socnet.2022.03.002

Publication date:
2023

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Social Networks, https://doi.org/10.1016/j.socnet.2022.03.002

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Abstract

Despite growing interest in the impacts of both forest certification and networks in effective natural resource management, there is little literature that brings these two lines of inquiry together. Combining longitudinal remote sensing and village-level forest governance network data, we estimate Cox proportional hazard models predicting the risk of forest loss within 100-square meter forest plots in areas that eventually came under Forest Stewardship Council certification. Our models indicate Forest Stewardship Council certification substantially reduces deforestation, despite that the system is not explicitly designed to do so. While villages with ties to civil society organizations also tend to experience reduced deforestation, those with ties to private sector organizations experience more forest loss. Further, we find that forest loss declines as the share of closed triangles in villages' governance networks increases. Our results indicate network structure may complement Forest Stewardship Council certification's impact on forest cover and account for some reduction in deforestation previously attributed to certification itself.

Introduction

Spurred by political contestation about the environmental and social impacts of global timber extraction in supply chains ending in Europe and North America (Bartley, 2007; Cashore, et al., 2004), there has been a significant expansion of third-party sustainable forestry certification programs. The Forest Stewardship Council (FSC) has become the most prominent global sustainable forestry certification standard (van der Loos, et al. 2018), and Forest Stewardship Council-certified forests now make up approximately 10% of total global forest cover.

Sustainable forest management is important for both global and local ecosystem service provision. A bit over a tenth of global greenhouse gas emissions are estimated to come from land-use and land-cover change (UNEP, 2020). Forest loss accounts for a substantial proportion of global land-use emissions (Pendrill, et al., 2019), but forest management planning, of the type required by Forest Stewardship Council certification, has been found to substantially reduce deforestation rates (Tritsch, et al., 2020). There is also evidence that Forest Stewardship Council-certified forests support higher carbon stocks than comparable forests (Charmakar, et al., 2021).

Scrutinizing how and under what conditions large-scale certification schemes can deliver on the promise of ecologically sustainable management is of high importance. Assessing the degree to which certification can protect forests, however, has proven exceedingly difficult. Not only are the potential direct and indirect impacts vast, but certification's effects are likely contextual, requiring complex research designs and extensive data collection to assess (Romero, et al., 2017; van der Ven & Cashore, 2018).

Combining longitudinal land-cover and governance network data, this study takes a novel approach to assessing the impact of Forest Stewardship Council certification on deforestation rates, disentangling certification's role as both an institution and a nexus of complex interorganizational relationships. Following a conventional definition, we think of institutions as the "rules of the game" (North, 1990) defining and regulating social activities. For our purposes, the fundamental rules of Forest Stewardship Council certification are the primary institution of interest. We define networks, by contrast, as reciprocal patterns of exchange and communication between actors (Powell 1990). Put briefly, institutions are rules, while networks are relations. Taking forest loss as a dependent variable, we use Cox proportional hazards models to assess the degree to which certification and network characteristics modify the risk of deforestation.

Embeddedness, which we define as how social actors are positioned within social networks, is one potentially critical but understudied correlate of certification's impacts. Research on embeddedness has offered a powerful framework for considering how individuals' and organizations' positions in networks of relationships can affect economic activities. Polanyi (1957) originally used the term to refer to the macro- and micro-level institutions shaping economic activities that transformed as translocal market connections emerged in early modern Europe. Granovetter's (1985) more recent usage of the term refers to how micro-level network configurations shape individuals' economic opportunities, prospects, and choices. Among many ways the concept of network embeddedness has influenced economic sociology and geography, it has stimulated a wave of research on how interfirm networks shape industrial districts, entrepreneurship, lending relationships, acquisitions, and performance (see Uzzi 1996 for a review). A key insight from this tradition is that firms' capabilities can improve as they build reciprocal ties with customers, clients, competitors, partners and regulators (Uzzi 1997; Powell 1990). Granovetter (1973), Burt (1992), and later Uzzi (1997), however, also point to a potentially risky aspect of network embedding: when organizations become too tightly embedded in networks, information and coordination tend to happen within closed social circles where group-think and a too-strong dependence on in-group resources can stymie innovation.

Researchers examining network governance of environmental concerns suggest effective network structures promise more efficient and equitable natural resource management and potentially support local buy-in to and social learning about conservation (Rudnick et al. 2019, Schnegg 2018, Bodin and Crona 2009, Bodin et al. 2017, Barnes et al. 2017, Pittman and Armitage 2019, Lauber, et al. 2008, Österblom and Bodin 2012, Zao and Wen 2012, Pretty and Smith 2004, Folke et al.. 2005, Schneider et al. 2003, Jones, Hesterly and Borgatti 1997, Gallemore et al., 2013, Henriksen et al., 2018, Ponte et al., 2017, Ponte, et al., 2020). These benefits, in turn, might be expected to help stem forest loss and other forms of environmental degradation.

Previous studies address two primary ways different aspects of network embeddedness might matter for areas undertaking sustainability certification to protect forests. On the one hand, dense, overlapping connections between actors, a pattern often called bonding, can support coordination and social trust. On the other, connecting actors in different sectors or communities, a pattern known as bridging, may provide access to new resources or ideas (Lauber, et al. 2008). Our understanding of bridging, to be clear, departs slightly from Granovetter's formulation, where bridges are defined in network structural terms (ties connecting dense cohesive clusters; Granovetter 1973). In the socioecological systems literature, by contrast, the term bridging often refers to crossing boundaries between sectors or communities of practice, as, for example, between governmental and civil society sectors, or natural, social, and traditional knowledge communities (Bodin & Crona, 2009; Cash, et al. 2006; Crona & Parker 2011, 2012). While these pools of knowledge might also be reflected in network structures, there is no guarantee that this is the case, so it is important to look for such instances of boundary-bridging explicitly.

There is considerable scope to investigate if and how bonding and bridging in environmental governance networks shape environmental outcomes like forest protection. While the first iteration of scholarship on networked environmental governance largely focused on overall network connectivity, more recent work differentiates particular network patterns, such as bridging and bonding, and relates those structures to governance performance, innovation, and learning (Barnes, et al., 2019; Bodin, et al., 2017). Network governance researchers expect networks to affect the capacity of both individual actors and the network as a whole to bring about sustainable outcomes (Bodin & Crona, 2009), but the bulk of the literature has focused on the latter relationship, usually using cross-sectional data (Bodin, et al., 2017; Enqvist, et al., 2020; Hamilton, et al., 2019; Kininmonth, et al., 2015; Sayles & Baggio, 2017; Sayles, et al., 2019). As Sayles, et al. (2019) argue, there is considerable room for research on environmental governance networks that relates network structures to outcomes. Two recent studies, for example, indicate bonding may support management quality and environmental outcomes (Barnes, et al., 2019; Bodin, et al., 2017). Bodin and Crona (2009) suggest that bridging between different groups may be important for effective information flows.

The different roles of bonding and bridging are also found, though often in different terms, in existing literature on Forest Stewardship Council certification. Not only is the Forest Stewardship Council itself a standard-setting process embedded in transnational networks mixing public and private organizations (Henriksen et al., 2016; Henriksen, 2015; Bartley & Smith

2010), local certification processes at production sites are embedded in networks linking local and transnational players. Local networks can foster trust and provide access to resources that support successful Community-Based Forest Management (Lauber, et al., 2008; Humphries, et al., 2020), while translocal networks may help forest managers access resources, skills, and knowledge (Baynes, et al., 2015; Humphries, et al., 2020).

While both the literature on Forest Stewardship Council and on network governance indicates the potential importance of both Forest Stewardship Council certification and social networks, disentangling this relationship is challenging. Strong bonding ties, for example, could facilitate trust and monitoring, helping improve Forest Stewardship Council performance, but this outcome could result simply from implementing certification rules themselves. Bridging ties, similarly, might provide access to resources and skills that facilitate certification, but certification itself connects actors to international markets and across the science-policy interface (da Silva, et al., 2019; Eden, 2009), facilitating bridging ties. Furthermore, communities themselves are increasingly "delocalized" (Ojha, et al., 2016), connected to transnational markets and politics that embed them in complex, translocal networks, and community members often also try to broker relationships with different external actors to influence local power struggles (Bartholdson & Porro, 2018; Górriz-Mifsud, et al., 2016). Finally, assessing the impacts of Forest Stewardship Council certification is challenging on its own. Certification is not randomly distributed, and selection effects, contextual interactions, and unobserved heterogeneity make assessments of the degree to which certification affects environmental outcomes difficult (Romero, et al., 2017; van der Ven & Cashore, 2018).

We address these methodological problems and contribute to the literature on Forest Stewardship Council certification and network governance by taking a temporal perspective. Combining longitudinal land-cover and governance network data documenting the co-evolution of forest cover and forest governance networks in Kilwa District in southeastern Tanzania, we estimate a series of Cox proportional hazard models that allow us to compare deforestation rates before and after four community forest areas achieved Forest Stewardship Council certification while controlling for unobserved sources of heterogeneity at the village level using frailty terms. We compare the estimated impact of Forest Stewardship Council certification and of bonding and bridging in our four study villages' governance ego networks, defined by all the organizations to which each village is connected and all the ties between these organizations. This approach allows us to assess the relative impact of Forest Stewardship Council certification and bonding and bridging.

We provide a brief background on community forest management and certification in the following section. After familiarizing the reader with this empirical context, we outline the methods used to assemble our longitudinal land-cover and governance network data and explain the logic behind our choice to analyze these data using Cox proportional hazards regression. Following a visual presentation of our primary statistical results, we argue that studying institutions' and networks' relative importance should be of interest to a variety of literatures on both social networks and natural resource management.

Empirical setting

Community-Based Forest Governance

Forest management in most countries in the Global South was characterized by top-down, state-centric governance for most of the 20th century. Starting in the 1980s, however, there was growing interest in more participatory approaches bridging corporate, civil society, and public actors with local decision making (Agrawal, 2005; Scheba & Muhtalahati, 2015). Like network governance, participatory management is generally thought to be more likely to support sustainable livelihoods and environmental outcomes (Gilmour 2016; Oldekop et al. 2019; Porter-Bolland, et al., 2012), but research assessing its impacts remains uncertain (Meijaard, et al., 2020).

Previous research suggests certified community-managed forests tend to provide more social and environmental benefits than non-certified forests, including improved governance and coordination, mild income increases, increased species diversity and richness, and more rapid reforestation (Burivalova, et al., 2016; Takahashi & Todo, 2012). Community forestry in general, however, should not be considered a panacea. There is considerable diversity across and within communities that affects the degree to which community forestry might be attractive, beneficial, or even applicable to any given group (Muttaqin, et al., 2019; Tole, 2010). Furthermore, effectively implementing community forest management requires skills and resources that often do not accompany the formal right to manage forests (De Royer, et al., 2018; Tole 2010). Arts and de Koning (2017) analyze ten community-based forest management cases across three continents using qualitative comparative analysis, finding evidence that community engagement, on its own, is insufficient to generate positive outcomes but that strong, high-trust relationships between external and internal actors are often associated with success. In the absence of trust, Kahsay and Bulte (2019) argue, rules can pick up the slack. Studying community forest management in Ethiopia, they find a negative correlation between trust and formalized governance rules.

Forest Stewardship Council Certification

The Forest Stewardship Council was an early entry in a wave of multi-stakeholder sustainability initiatives, born out of disappointment that the 1992 Earth Summit did not adequately address deforestation (Moog, et al., 2015). As a market-based initiative, Forest Stewardship Council certification is only effective to the extent that market actors are motivated to seek out sustainable timber sources and the certification is understood as legitimately rigorous (Eden, 2009). Organizations like the Forest Stewardship Council, therefore, must carefully balance demands for stringency with desires for expansion. More stringent standards generally will impose higher costs and be harder to articulate with existing legal frameworks, and the Forest Stewardship Council has struggled to expand certification outside more affluent countries with well functioning institutions (Bartley, 2010; Marx & Cuypers, 2010).

To receive Forest Stewardship Council certification, forest managers must adhere to a set of ten Principles and Criteria established by the organization, as interpreted through national or regional standard development groups consisting of Forest Stewardship Council members. Small operators may collaborate to receive group certification (Forest Stewardship Council International, nd). To provide credibility that certified forest managers are in fact adhering to the Principles and Criteria, third-party Certification Bodies are approved by the organization to conduct on-site audits. These audits include sampling of forest area, interviews, document collection, stakeholder engagement, and other procedures, ultimately resulting in a report detailing patterns of compliance and non-compliance with the Forest Stewardship Council's basic rules.

Forest management in Tanzania

As Bartley (2011) notes, private governance systems like the Forest Stewardship Council can be thought of as a "layering of rules" atop existing national regulations. Understanding their effects, therefore, also requires considering the historical context into which they are inserted. Before the colonial period, Tanzanian forests were regulated primarily by customary law (Barrow et al., 2002; Kajembe et al., 2005). Managed forests were spiritually important and governed as commons, supporting local livelihoods with resources like food and medicine (Zahabu et al., 2009). When colonial powers expropriated indigenous lands, however, they imposed new legal and tenurial arrangements (Malimbwi and Munyanziza, 2009). Under first Germany and then Britain, colonial administrations supported timber extraction, and, later, plantations. The colonial powers also brought Western forest management practices, new production methods and assumptions about "conservation" that restricted locals' forest access and use. In 1904, the German colonial power issued an ordinance establishing forest conservation reserves (Kostiainen, 2012), which the British Mandate further expanded (Kajembe et al., 2005). In 1953, the Mandate introduced the first Forest Policy and in 1957 the first Forest Ordinance, further restricting protected forest areas and consolidating government control of forest resources (URT, 1998). Even following independence in 1961, the National Forest Policy of 1963 retained several colonial policies. Forest management remained centralized, with no ownership or management authority allocated to the local communities (Kalumanga et al. 2018).

Eventually the National Forest Policy of 1998 and the Forest Act of 2002 acknowledged private actors' and local communities' key roles in forest management (URT, 1998; URT, 2002). The move to Community-Based Forest Management (also often referred to as Participatory Forest Management), allowed villages to take over ownership of Village Land Forest Reserves

(VLFRs) and co-manage part of National Forest Reserves under Joint Forest Management programs (Blomley and Iddi, 2009: 6). As of 2015, 55% of the Tanzanian mainland was classified as forest. Production forest, in turn accounted for 40% of total forest area (NAFORMA, 2015). Today, more than 60 districts are involved in Joint Forest Management, and there are about 50 Village Land Forest Reserves (Kalumanga et al. 2018).

Because of its widespread implementation via Joint Forest Management and Community-Based Forest Management, there has been considerable scholarly interest in Participatory Forest Management in Tanzania. The vast literature on decentralized forest management in the country suggests community management performs comparably to or better than state-managed areas in terms of net forest cover and overall forest quality (Mbwambo, et al., 2012; Uisso, et al., 2019). Impacts on livelihoods, however, appear small or negligible in comparison to changes in agricultural market prices and other economic opportunities (Corbera, et al., 2017; Gross-Camp, 2017; Vyamana, 2009). As with many integrated conservation and development approaches, several studies of Tanzanian Community-Based Forest Management raise concerns about how local power structures and corruption can undermine these initiatives, leading to elite capture, poor benefit sharing, increased costs for the least affluent, and even outright violence (Bluwstein & Lund 2018; Brockington, 2007; Gross-Camp, et al., 2019; Lund & Saito-Jensen, 2013; Magessa, et al., 2020; Meshack, et al., 2006; Ngaga, et al., 2013; Rantala, et al., 2012).[1]

Contemporary forest management in Kilwa

Villages in Kilwa District in southeastern Tanzania started developing Community-Based Forest Management in the 1990s (Treue et al. 2014). In the early 2000s, the Mpingo Conservation Program, now the Mpingo Conservation and Development Initiative (MCDI) began work to facilitate certified sustainable blackwood (*Dalbergia melanoxylon*; *mpingo* in Kiswahili) harvesting. MCDI has since been a key supporter of and broker for Kilwa's Community-Based Forest Management efforts, working alongside governmental, private sector, and civil society organizations. The organization continues to focus on Forest Stewardship Council certification as

[1] For a more expansive background on forest management in Tanzania, see Kalumanga et al. 2018.

a way for communities to benefit from forest conservation (Ponte et al. 2017). The Kilwa District Council has for some time received financial support for Community-Based Forest Management directly from the Ministry of Natural Resources's National Forest Programme and indirectly through NGOs like MCDI and World Wildlife Fund (WWF) to support these efforts. Mirroring findings on Community-Based Forest Management in Tanzania more generally, Treue et al. (2014) studied 12 forests in Kilwa and found that Village Land Forest Reserve areas tend to be better managed than open-access areas but that extraction rates depended largely on location and types of local use.

While there have been notably fewer studies of Forest Stewardship Council-certified Community-Based Forest Management in Tanzania than of Community-Based Forest Management more broadly, several of those that do exist focus on MCDI-supported villages in Kilwa District. Here, there are indications that certification has positive environmental benefits and may also help address some of Community-Based Forest Management's institutional shortcomings, helping avoid elite capture and improve equity (Khatun, et al., 2015). Kalonga, et al. (2015, 2016) find that Forest Stewardship Council-certified forests in Kilwa District have higher adult tree species density, diversity, and richness than open-access or state forests. Corbera, et al. (2017) find substantially improved forest governance (e.g. better coordination, forest management and social cohesion) in Forest Stewardship Council-certified villages working with MCDI in Kilwa. These improvements, however, have not translated into statistically detectable impacts on livelihoods or assets. Also in Kilwa, Kalonga and Kulindwa's (2017) comparative economic valuation study shows households receive significantly higher income from certified than non-certified Community-Based Forest Management operations. Further, they find much better implementation of forest bylaws in certified forests. Kalonga, et al. (2014) also find slightly lower income inequality in certified versus non-certified operations in Kilwa.

Case selection

Today, 14 Village Land Forest Reserves have been formed in Kilwa, representing an estimated 43.6 % of the total land managed as Village Land Forest Reserves across the country (Bwagalilo et al., 2019). Between 2010 and 2014, the MCDI in collaboration with the Kilwa District Council and other actors helped villages implement Community-Based Forest Management in their Village Land Forest Reserves as part of a pilot program under Reducing Emissions from Deforestation and Forest Degradation (REDD+). Kilwa's REDD+ pilot provided various types of support (e.g. financial, technical, etc.) for Community-Based Forest Management and forest certification, attracting a new layer of state and non-state actors with a stake in sustainable forest management. In general, Village Land Forest Reserve management stimulated interest in multi-stakeholder, collaborative governance. At the same time, the MCDI secured a Forest Stewardship Council Group Certification Scheme for the villages that implemented REDD+ in their Village Land Forest Reserves. Of Kilwa's 14 Village Land Forest Reserves, 11 are currently under MCDI's Group Certification (Bwagalilo et al., 2019; see Table 1).

Given the extensive data collection required to map village resource governance networks from prior to Village Land Forest Reserve establishment to after Forest Stewardship Council certification, we decided to focus on a sample of four villages: two early movers (Kikole and Nainokwe) and two late movers (Likawage and Mchakama). These four villages also encompass a range of very small, small, medium-sized, and large Village Land Forest Reserve areas. We present a map of Kilwa with the boundaries of our study villages and their Village Land Forest Reserves in Figure 1.

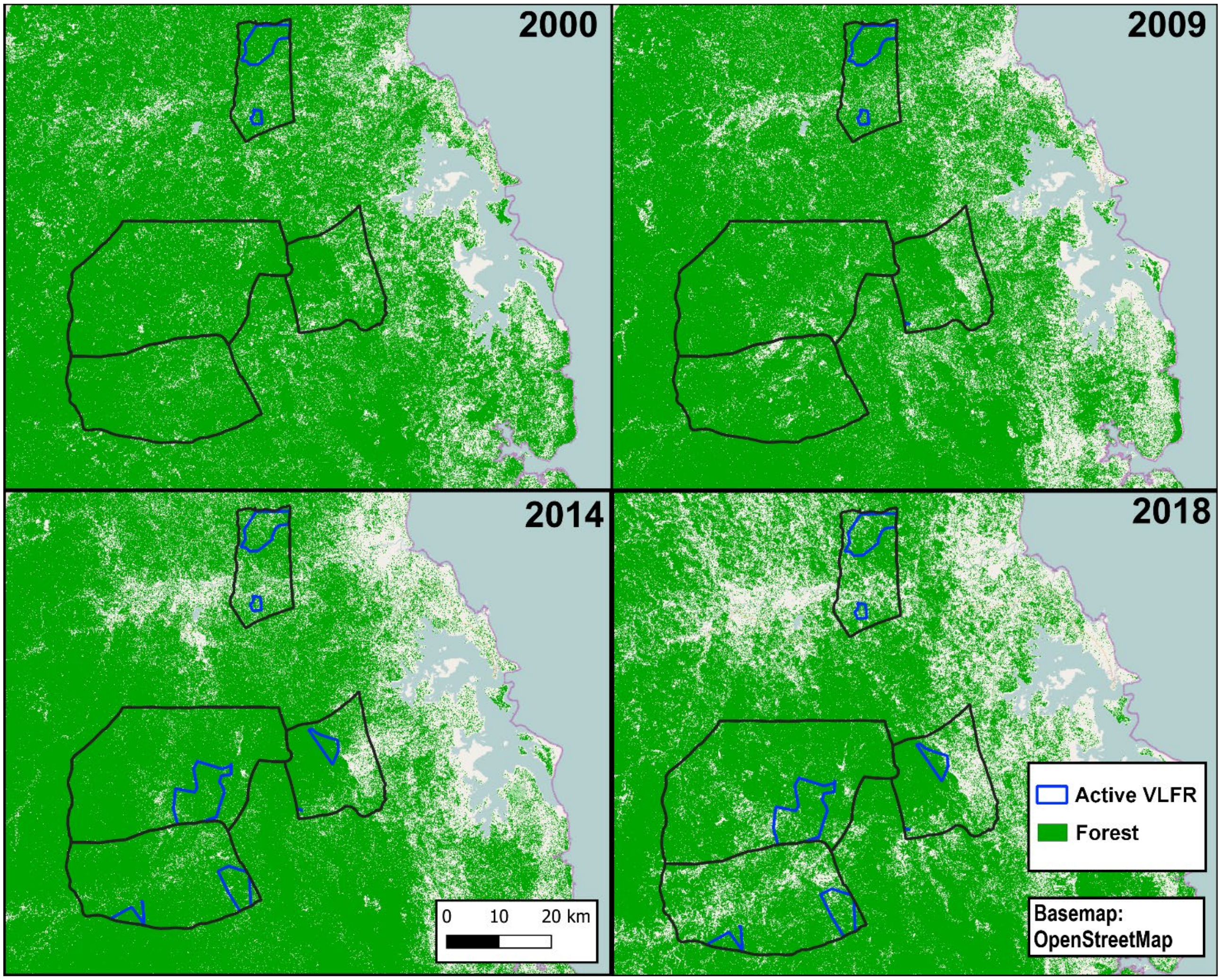

Figure 1. Study areas that become Village Land Forest Reserves (VLFRs) in Kilwa District, Tanzania, with forest cover.Starting in 2009, all depicted VLFRs are also Forest Stewardship Council (FSC) certified. Projection: UTM Zone 37S. Data from the Government of Tanzania, land cover classification data described in the Appendix, and the Mpingo Conservation and Development Initiative. Basemap: OpenStreetMap.

Village	VLFR start year	Forest area (Ha)	FSC cert. year	Sample village
Kikole	2004	454	2009	Yes
Kisangi	2005	1,966	2009	No
Nainokwe	2009	8,047	2010	Yes
Liwiti	2009	6,229	2010	No

Likawage	2013	19,624	2013	Yes
Ngea	2013	1,893	2014	No
Nanjirinji A	2013	61,505	2013	No
Nanjirinji B	2013	18,963	2016	No
Mandawa	2013	1,994	2014	No
Mchakama	2013	1,525	2014	Yes
Namatewa	2016	6,748	2017	No

Table 1. Overview of VLFR / FSC certified villages in Kilwa (source: Kalumanga et al. 2018)**.**

Data and methods

We combine remotely sensed land-cover and other geographic data for four time periods with ego network data identifying study villages' embeddedness in forest governance networks. Using Cox (1972, 1975) proportional hazards regression models, we estimate the association between 10-meter by 10-meter forested areas' risk of deforestation during an observation period, our dependent variable, and our independent variables of interest, measures of villages' network embeddedness and the onset of Forest Stewardship Council certification. We use the Cox model to control for geographic factors that may contribute to deforestation, as well as village-scale heterogeneity. Because our data come from diverse sources and have been processed using techniques that may not be fully familiar to a network analysis audience, we provide an overview of our data processing and analysis methods in Figure 2 and unpack each of these components in the following subsections.

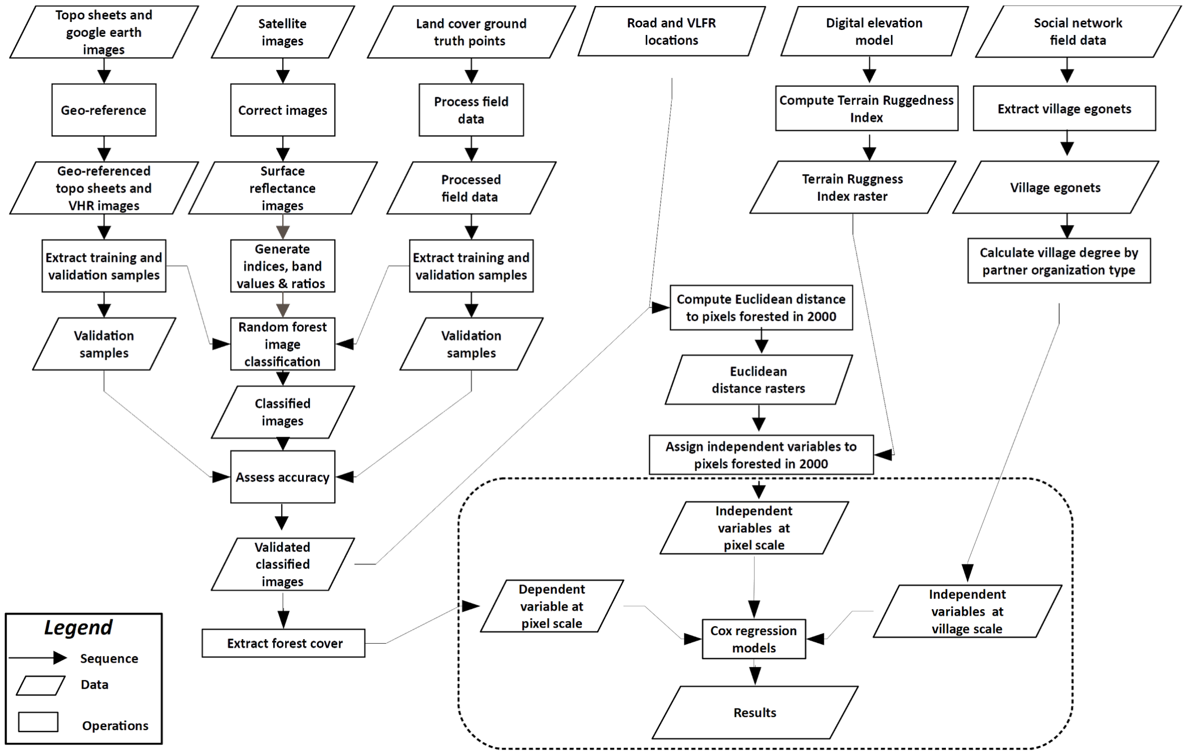

Figure 2. Flowchart of data processing operations.

Land-cover variables

To identify deforestation in our study villages, it was necessary first to develop a dataset showing changes in land cover across Kilwa district. For this purpose, we turned to openly available remote sensing data from Sentinel and Landsat satellites, which often are used to detect changes in land cover (Chander, et al., 2009; Haeusler, et al., 2017; Rüetschi, et al., 2019). As this is a quite technical process, we summarize the research implications of our methodological choices here and present a more technical description in the Appendix.

Because satellite images only measure how much radiation the satellite sensors detected at various bands in the electromagnetic spectrum, it is necessary to classify combinations of these values into discrete groups indicating different types of land cover. We used supervised classification to translate our remotely-sensed imagery into 10 meter by 10 meter resolution raster datasets showing discrete land-cover types (barren, cropland, human settlement, grassland, woodland, coastal forest, and water). While the two forest types (woodland and coastal) are ecologically distinct, we combined them into a single forest class for the purpose of analysis.

Supervised classification requires generating a set of training data, locations of known land-cover type that can then be used to train machine-learning algorithms that are able automatically classify the millions of pixels in the remotely-sensed imagery. We conducted fieldwork to collect training points, augmenting these with existing maps of known land cover at different times, as well as image interpretation using very high resolution Google Earth imagery. While it might have been ideal to collect all training points in the field, supplementing field-collected points with these other sources allowed us to generate training points across a larger spatial extent than would have been feasible with fieldwork alone. It also permitted us to work iteratively with the classification algorithms, collecting further training points for land-cover types that were more frequently confused to increase classification accuracy. We provide details on the most accurate classification achieved, which we use for the models reported in this paper, in the Appendix.

Because geographic context has a strong effect on the likelihood that a pixel is deforested, controlling for forest plots' surroundings is critical (Panlasiqui, et al., 2018). Using ArcMap, we computed for each forested pixel in 2000 the Euclidean distance to the nearest settlement, cropland, and forest edge pixel, in kilometers, for each year it remained forest. Because the landscape in the area is changing over time, these values are often different for the same pixel across time periods. As a further control, we computed the Euclidean distance to the nearest major road passing through Kilwa. Finally, using a 30-meter resolution digital elevation model from the Shuttle Radar Topography Mission (Farr, et al., 2007), we computed the Terrain Ruggedness Index (Riley, et al., 1999) around each pixel that was forested in 2000. These latter two variables remain constant over time, as there were no major construction projects or topographic changes during the observation period.

Forest Stewardship Council onset variable

We obtained shapefiles of villages' Village Land Forest Reserve boundaries as of early 2020 from MCDI and by creating polygons for some boundaries using coordinates reported in MCDI's publicly available Forest Stewardship Council management reports (MCDI, 2020). Due to ongoing boundary confusion in the region, some Village Land Forest Reserve boundaries extended outside the village claiming management authority. Because of the ambiguity of these situations, we excluded these areas from analysis. Consulting the village management plans required for Forest Stewardship Council certification posted on MCDI's (2020) website, we identified the year each Village Land Forest Reserve achieved Forest Stewardship Council certification. Using this information, we constructed variables identifying, for each study area, whether or not it was Forest Stewardship Council certified during the observation time period.

Network variables

We follow our study villages' embeddedness in forest governance networks across four time intervals covering years up to, during and following Village Land Forest Reserve and Forest Stewardship Council implementation (2000-2004, 2005-2009, 2010-2014, and 2015-2018). Using several event- and document-based sampling strategies and respondent-driven link-tracing approaches well-known to network research (Heckathorn and Cameron 2017), we collected social network data characterizing the network of organizations engaging in business, technical, and governance collaborations on forest-related issues in our study villages, as well as the connections between village governance organizations and these other actors. We coded all identified partners into three mutually exclusive organisational types: government, private sector and NGOs.

Our network data is intended to capture formal, interorganizational collaboration, such as common participation in a development or capacity-building project, partnership in a community forest enterprise, or business development activities. Because these kinds of activities leave historical records, we triangulated information from village guestbooks, documents, and oral histories to reconstruct these networks as completely as possible. First, all village visitors are obliged to sign the village guestbook, which records visits from corporations, NGOs, donors, and government officials. Consulting guestbooks as far back as those records were available in each village provided an initial organization-to-village network. Second, to fill in potential omissions due to missing guestbooks, recording lapses, or collaboration that did not involve direct village visits, we consulted policy and conservation project documents obtained from national archives, expert interviews, and online research. We used these materials to code time-stamped collaborative relationships, adding new organizations encountered to the list of village partners constructed from the guestbooks. Third, the team interviewed representatives from Village Councils and Natural Resource Committees about the organizational partners with whom they had collaborated on sustainable forest management, as well as the villages' external partners, in order to document relationships from both sides of the dyad. The existing list of partners from the guest books and documents informed these interview questions, and we asked respondents to elaborate on the nature of specific collaborations and identify further partnerships not yet on the list. Informants, further, provided information on the timing of collaborations according to the periodization outlined above. While this approach is unlikely to capture every relationship in the governance network, it is likely to capture the most important ones. Any bias in the data collection is likely to fall on the side of omission, rather than overinclusion.

To construct our network-based independent variables, we focused on our study villages' ego networks, an approach consistent with other studies examining network effects on environmental management (Barnes, et al., 2019; Bodin, et al., 2017). Keeping our measures simple, we computed, for each time interval, the number of civil society and private sector organizations with which each village collaborated, a measure known as degree in social network terms. For estimation purposes, we added one to each degree measure and then took the natural logarithm, anticipating declining marginal effects with additional partners from the different sectors. We interpret villages' private sector and civil society degrees to indicate the extent to which village actors bridge across distinct interest spheres. While we documented village ties to government organizations, as our village actors are themselves governmental, we do not consider village ties to other government entities as bridging in the sense defined at the outset. They are, however, relevant to bonding, so we include ties with all organization types in computing our bonding indicator. For this, we use the percentage of closed triads, or sets of three nodes in which all nodes are connected to each other.

Estimation technique

Our goal was to model the risk of deforestation as a function of whether a forest plot is Forest Stewardship Council-certified and it, along with network embeddedness, affect forest loss. Because we were interested in how deforestation risk changes over time under various conditions, we estimate Cox proportional hazard models, commonly used to model time-to-deforestation data (Busch & Vance, 2011; Reid, et al., 2019; Vance & Geoghegan, 2002). This technique is more attractive than similar techniques, like logistic regression, for three primary reasons.

Cox models are an attractive method, first, because our units of analysis are 100-square-meter plots identified as forest in 2000 which at some later period become Forest Stewardship Council certified. While this before-and-after treatment comparison allows us to focus on the impact that changes in institutional and social network characteristics have on forest-cover change, unobserved heterogeneity at the village level could still make identification challenging. Conventional regression models including Cox regressions assume that the units of analysis in a sample are independent of one another. Yet, units that are nested within the same higher level cluster (in our case villages) are likely to be affected by unobserved village-scale differences, violating the independence assumption. To mitigate this problem, we include village-level frailty terms in our Cox regression models. Frailty terms can be thought of analogously to random-effect terms in panel regression models - in our case, they capture unexplained village-level heterogeneity in deforestation risk. While it might be possible to estimate a series of other village-level control variables instead of frailty terms, frailty terms have the advantage of capturing all unexplained village-level heterogeneity, making them more likely to address omitted variable bias than even multiple control variables.

Second, this modelling approach helps us address the risk of selection bias - that is, the possibility that there might be something systematically different about areas that are eventually Forest Stewardship Council certified that also affects their deforestation rates. Using Cox models with frailty terms with the specific dataset we employ helps address this problem in a few ways. First, observing only areas that ultimately become Forest Stewardship Council-certified community forests avoids selection biases from geographic factors that might make one area more likely to become certified than another. Second, because the frailty terms capture unexplained village-level heterogeneity in deforestation risk, they also should capture any non-time-varying omitted variables that could simultaneously affect both deforestation and the propensity to become certified. Finally, because we observe forest change in these areas before and after Forest Stewardship Council-certification, we can have reasonably high confidence that the coefficients we estimated are unlikely to be due to selection effects or omitted variable bias.

Third, Cox models permit time-varying covariates, which is particularly important not only because our Forest Stewardship Council and network terms vary, but also because Kilwa is a dynamic landscape characterized by swidden cultivation, so most of our geographic control variables change over time, as well. This is important because we would naturally expect deforestation risks to be higher closer to the forest edge. To the extent that forest edges will shift with cycles of crop clearance, fallowing, and regrowth, it is necessary to use a model that allows us to incorporate information about these dynamics into the estimation process. Using the frailty terms to keep non-time-varying village-level characteristics fixed, time-varying geographic controls (in this case, all the control variables except terrain ruggedness and distance to a main road) then help us to control for relevant time-varying factors driving forest loss.

This modeling approach does have a few drawbacks, though these are quite common in land-cover-change research. Because there are so many factors that impinge on land-cover change, isolating the relationships between any given set of variables requires us to try to hold many other sources of variation constant. Hence, using the village-level frailty terms and time-varying geographic controls means that we are using network and institutional variables to explain primarily temporal - rather than geographic - differences in deforestation rates. However, we see this as a way to design a quite conservative estimate of these key independent variables' relationship with deforestation. That is, the research design could lead us to underestimate the true effects of these factors on deforestation, but it is unlikely to overestimate them.

Biomass Estimation

While forests have many positive benefits, they are also an important component of climate change policy, both as a site of carbon sequestration and, when deforested, of emissions. To make the implications of our findings for climate change clearer, we draw on a nation-wide dataset constructed by researchers based at the University of Edinburgh that estimates above-ground woody biomass at a 25-meter resolution for the entire country in 2007 and 2017 (McNicol, et al., 2018). Because these years overlap, but do not correspond with, the years of our remote-sensing data, we developed a strategy to use them to estimate the biomass in forested patches in our study area. First, we identified pixels from our remote-sensing data that were forested before and remained forested after each of the available biomass years. We then intersected these pixels with the biomass layer for the year to which they were closest. Next, we combined the biomass estimates for both layers of pixels to compute the expected mean biomass, in tons of carbon per hectare, for forested pixels in our study area. Finally, we used this value to estimate the predicted change in total landscape woody biomass resulting from forest change in our model simulations.

Results

Descriptive statistics

Table 2 presents basic descriptive statistics for variables used to estimate our Cox models. By the end of our observation time period in 2018, 9.6% of the 1,753,578 10-meter by 10-meter forested areas in our study areas were deforested, amounting to a total of 5,912 hectares. This aggregate measure hides considerable heterogeneity across villages, clearly visible in the village forest loss curves shown in Figure 3. By the end of the observation period, the forest loss rate for Mchakama, the most successful study area, is roughly 20 percentage points lower than Kikole, our least successful village.

Continuous Variables						
Variable	Mean	Std. Dev.	Min.	Max.	Role in Models	Source
Village Civil Society Degree (ln)	1.50	0.765	0	2.57	Network variable	Field network data
Village Private Sector Degree (ln)	0.991	0.938	0	2.56	Network variable	Field network data
Triangle Percent	28.5	35.9	0	100	Network variable	Field network data
Distance to Cropland, M (ln)	5.09	1.08	0	7.63	Control variable	Remote sensing data
Distance to Built Up, M (ln)	7.28	0.749	0	8.59	Control variable	Remote sensing data

Distance to Forest Edge, M (ln)	4.30	1.01	0	7.19	Control variable	Remote sensing data
Distance to Road, M (ln)	8.73	0.878	0	9.76	Control variable	Remote sensing data
Terrain Ruggedness Index	1.63	1.40	0	16.5	Control variable	Shuttle Radar Topography Mission
Binary Variables						
Variable	0 Value	1 Value	Percentage of 1s		Role in Models	Source
Deforested	Forested	Deforested	10%		Dependent variable	Remote sensing data
FSC Active	Inactive	Active	50%		Institutions variable	MCDI
Forest Type	Coastal	Woodland	46%		Control variable	Remote sensing data

Table 2. Descriptive statistics for dataset used to estimate Cox models. N = 1,753,578 plots and 6,171,114 plot-period observations. Variables marked with ln are expressed in terms of logarithms to base e.

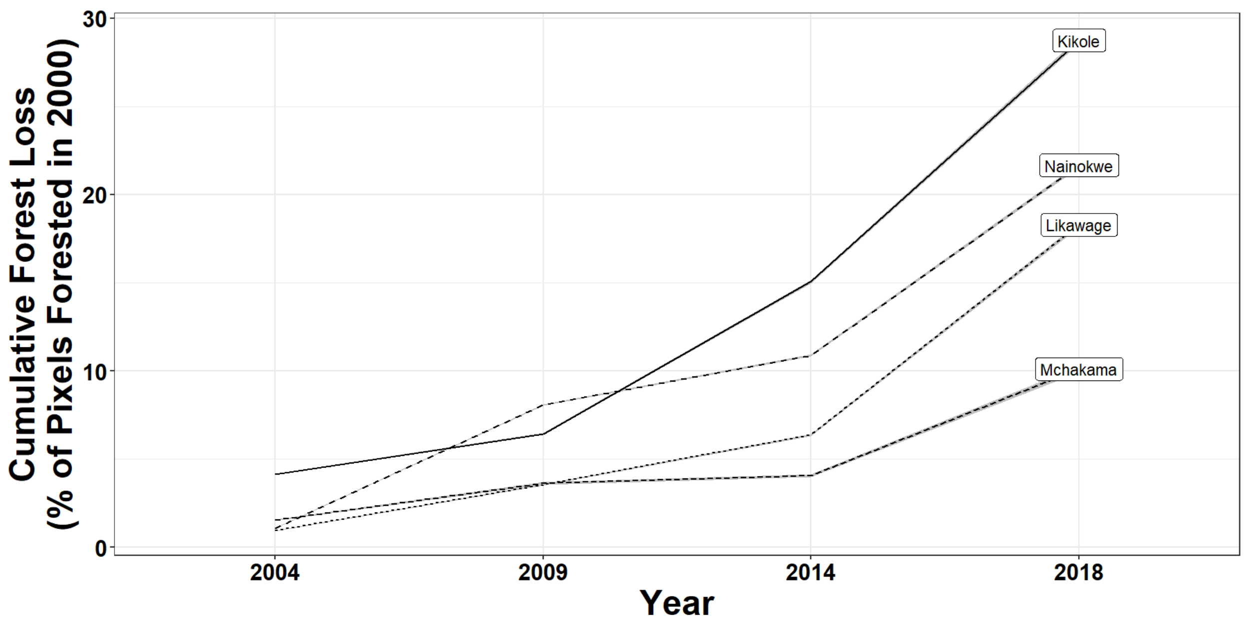

Figure 3. Cumulative forest loss percentage, by village, for ten meter by ten meter pixels that were forested in 2000. This measure does not reflect any forest regrowth in the study areas. The figure shows 99% confidence intervals, but these are generally more narrow than the width of the line selected for visibility.

The divergence across villages is not readily explained by the timing of Forest Stewardship Council certification alone. Certification was active for slightly over half (51.4%) of our pixel-year observations, but certifications become active at different times across villages. Kikole achieved certification in 2009, the first of the study villages to do so. Mchakama achieved certification last, in 2014.

The villages' ego networks also vary considerably in composition and structure across both space and time (Figure 4). While ego networks generally expand over time, there are several instances in which network size declines in the final time period, leading to fewer partners with more triadic closure (that is, more sets of three nodes in which each node is connected to the others). This pattern is consistent with our field observations and contextual knowledge about the process of enrolling the villages in the Forest Stewardship Council certification process. As villages were enrolled in the certification process, they started forming partnerships with government, private and civil society organisations. Generally, village ego networks were most expansive and diverse around the time they achieved certification. Some of the villages' external partnerships involved funding schemes, some had to do with training and technical assistance, and some were concrete governance collaborations. As time passed, some of these partnerships became obsolete. The villages also vary in terms of network composition. Likawage, for example, had a dense private sector network in and around the time of certification, whereas Kikole and Mchakama had a dense civil society network. Mchakama was the only village to witness a dense government network, and in this case the growth of government organizations largely covaried with the growth of civil society organizations. For this reason, and because ties to governments conceptually do not constitute bridging ties in the sense outlined in the introduction, we ignore the role of government ties in our analysis of bridging.

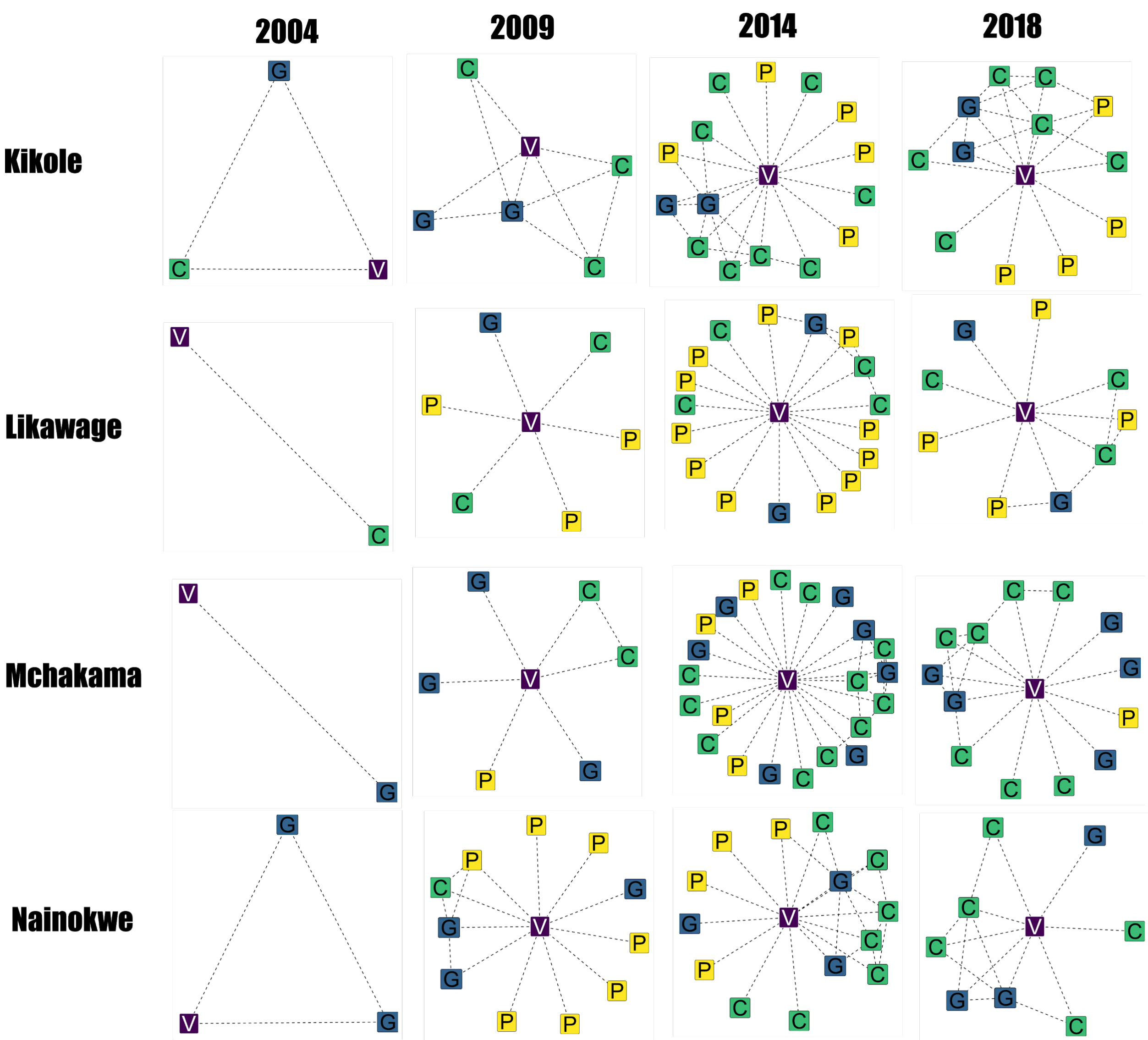

Figure 4. Observed village governance ego networks, projected using Fruchterman-Reingold algorithm, which locates organizations connected to more common partners closer together. V = Village; G = Government; C = Civil Society; P = Private Sector.

In addition to these sources of heterogeneity, our study areas differ geographically, resulting in differential exposure to deforestation drivers (Figure 5). Because Kilwa is a dynamic landscape characterized by swidden cultivation and infrastructure development (McNicol, 2015) all geographic variables other than the Terrain Ruggedness Index and the distance to main roads vary across time, and all of these variables differ across study villages. Forest pixels in Mchakama, our best-performing village, for example, tend to be on more rugged terrain, in larger forest patches, and further from built-up areas than the village study areas taken as a whole. Pixels in Kikole are notably closer to cropland than in other villages but are also in more rugged terrain and further from an improved road.

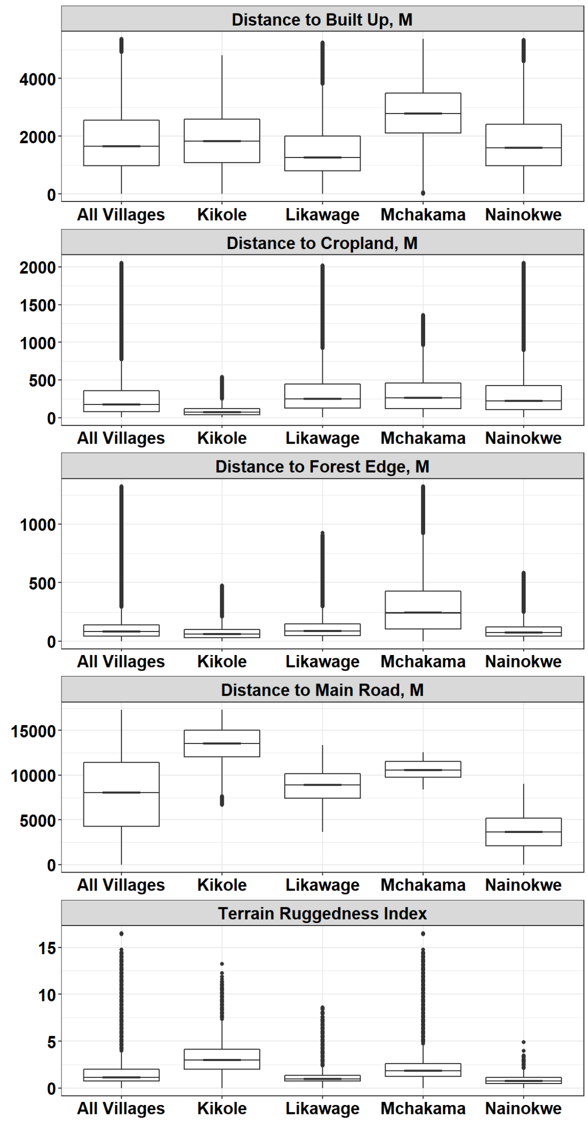

Figure 5. Boxplots showing differences in geographic control variables across villages. “All villages” category shows the distribution for the entire sample.

Cox proportional hazards model analysis

To better understand the relationship between Forest Stewardship Council management and our network measures, we estimated a series of Cox models including different combinations of independent variables with and without frailty terms, recording the concordance of each model to compare fit (Figure 6). Concordance compares a random sample of pairs of observations, one in which deforestation occurred and one in which it did not, computing the proportion of the times the model estimated the deforested pixel to have the higher risk of deforestation. This allows us to compare changes in model fit resulting from the addition of different groups of variables, with values closer to one indicating better fit.

To allow for comparison, we estimate models including only variables identified as controls in Table 2; models with these variables and all variables identified as network variables in Table 2; control variables and whether or not Forest Stewardship Council is active; models with controls, Forest Stewardship Council activity, and each of the network variables separately; and models with Forest Stewardship Council activity and all the network and control variables in Table 2. For each configuration of variables we estimate models with and without frailty terms, which control for unexplained heterogeneity at the village scale, as well as a model with only the frailty term. Decomposing the models this way allows us to compare the relative contribution of different sets of variables both to overall model fit and to predicting cross-village heterogeneity.

As expected, models with frailty terms consistently have better model fit than corresponding models without these terms, suggesting it is very important to adjust for village heterogeneity, likely for the numerous reasons noted above. Figure 6 indicates that the combination of all of our network variables tends to better explain variation in forest loss at the village level than the Forest Stewardship Council term alone, as can be seen from the higher concordance for the model with all the network variables as compared to the model with only Forest Stewardship Council activity. While this difference is most pronounced in non-frailty models, it remains, though is slight, when the frailty term is included. As expected, however, the model with all our independent variables and a frailty term has the highest concordance (and lowest Bayesian Information Criterion, another measure of relative model fit) of our estimated models, so we focus on it in our interpretation.

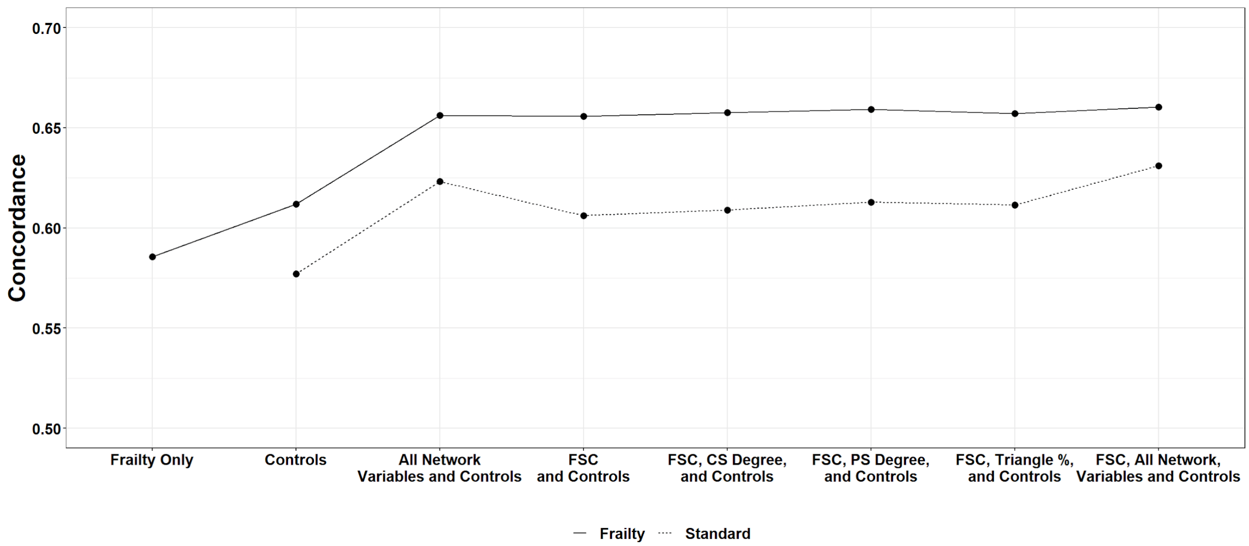

Figure 6. Concordance measures for all estimated models. Concordance measures the share of pairs of observations in which deforested observations were estimated to have a higher probability of deforestation than non-deforested observations. CS = Civil Society; PS = Private Sector.

To make our interpretations more concrete, we present our results in terms of predicted changes in forest biomass under different scenarios, based on the coefficients from our best-fitting model. We present a coefficient plot for this model in Figure A1 in the Appendix. Figure 7 provides evidence that collinearity with network embeddedness measures accounts for a small but discernible portion of Forest Stewardship Council certification's estimated impact on forest loss. As Figure 7 demonstrates, the predicted difference in forest loss between certified and uncertified areas declines when the model includes network measures (that is, the points for simulations where observations are Forest Stewardship Council certified are closer to the points where the observations are not), particularly when controlling for the number of private sector actors in a village's ego network, suggesting collinearity with network embeddedness measures may account for some of Forest Stewardship Council certification's estimated effects. While noticeable, however, the decline is very small as a proportion of Forest Stewardship Council's total estimated effect. Improvements in network structure appear to supplement Forest Stewardship Council's role in slowing forest biomass loss in Kilwa, rather than explaining it.

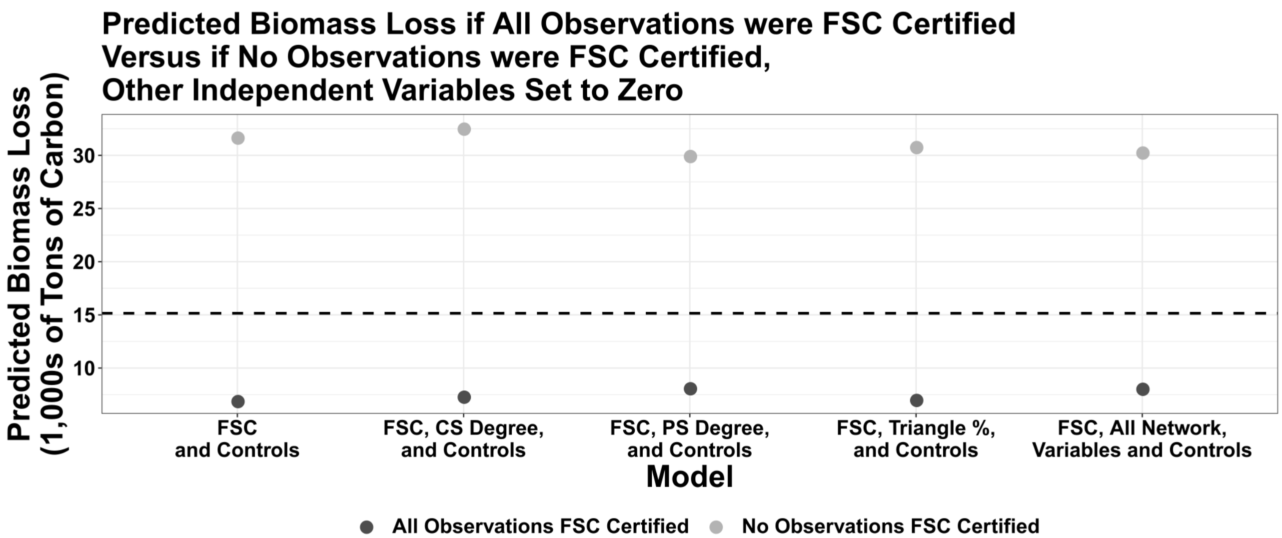

Figure 7. Predicted biomass loss if FSC certification were active in all study areas for all time periods, compared to if no FSC certification were active in any study area or time period, by model. All other independent variables are set to zero. Dotted line shows observed biomass loss estimate. Values calculated using the coxsimLinear function in the simPH package (Gandrud, 2015) to compute 1,000 simulated survival rates from each model. Points show the mean predicted biomass loss in each condition.

Even controlling for network effects, Forest Stewardship Council certification's estimated impact on forest loss remains quite substantial. To give a sense of this effect, the histogram in Figure 8 shows the predicted increase in forest survival for certified versus non-certified forest pixels, calculated from the model with all independent variables for each observation. The distribution indicates a substantial impact, which varies with both network and control variable values. Across all observations, we estimate Forest Stewardship Council certification to lead to a median 14- and a mean 17-percentage-point increase in the probability that a forest plot escapes deforestation. For 50% of our observations, in other words, Forest Stewardship Council certification increased their predicted survival probability by more than 14%.

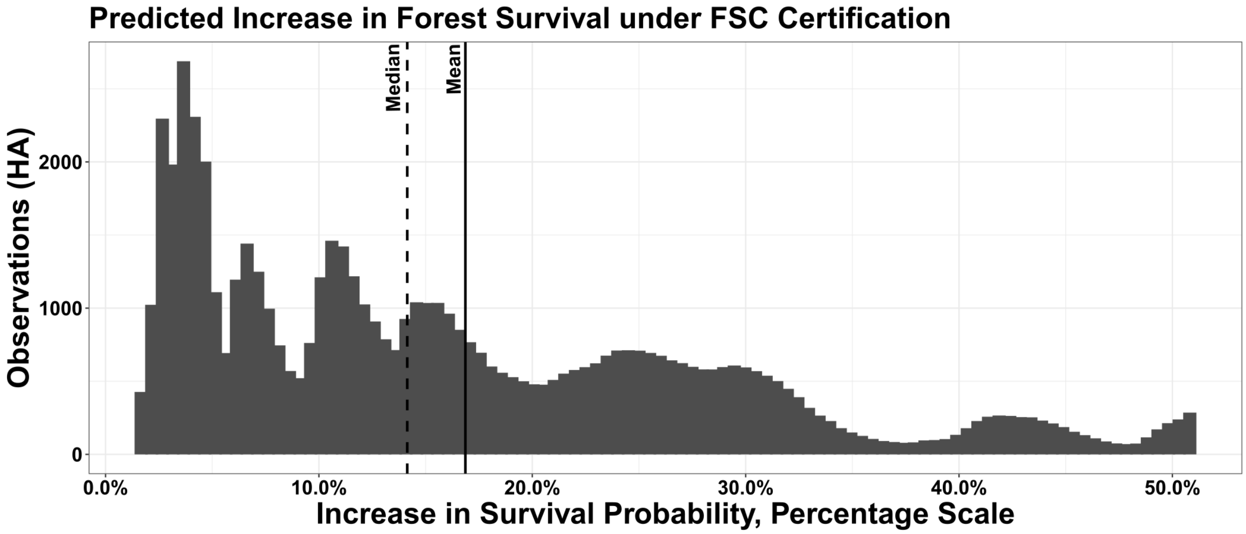

Figure 8. Predicted increase in forest survival probability, on a percentage scale, if a 10 meter by 10 meter pixel is under FSC certification compared to the same pixel without certification. Computed for every pixel-year observation using the model with FSC certification, all network variables, and controls. Vertical lines show the median and mean predicted differences in survival probability.

Turning to the network embeddedness measures, we find, as anticipated, that both bridging and bonding are associated with differences in deforestation rates. However, we also find that the impact of bridging depends on the partner's sector. While increases in Village Civil Society Degree are associated with lower predicted forest loss, the opposite is true for Private Sector Degree. To put these differences in context, Figure 9 shows changes in the predicted total biomass loss in a variety of scenarios constructed by setting all observations to values across the range of each of our network variables, with all other variables held at zero. For these simulations, we use coefficient estimates and standard errors from the model including all our independent variables. Based on these simulations, if we moved every forested pixel from a Civil Society Degree of zero to the maximum observed value, we would predict a decrease in total biomass loss of about 17%. By contrast, if we did the same for Private Sector Degree, we would expect an increase in biomass loss of about 11%.

Bonding, measured as the percentage of closed triangles, or the percentage of all groups of three nodes in each ego network that are all connected, given that two of the nodes are connected to the third, appears to be associated with decreased deforestation in a manner similar to Civil

Society Degree. A move from a village ego network with no closed triangles to one composed entirely of closed triangles, for example, results in a predicted reduction in biomass loss similar in magnitude to that observed for a move from the minimum to maximum Civil Society Degree. More realistically, a move from a network with no closed triangles to a relatively common value of 25% closure is associated with an estimated reduction in total biomass loss of approximately 7%.

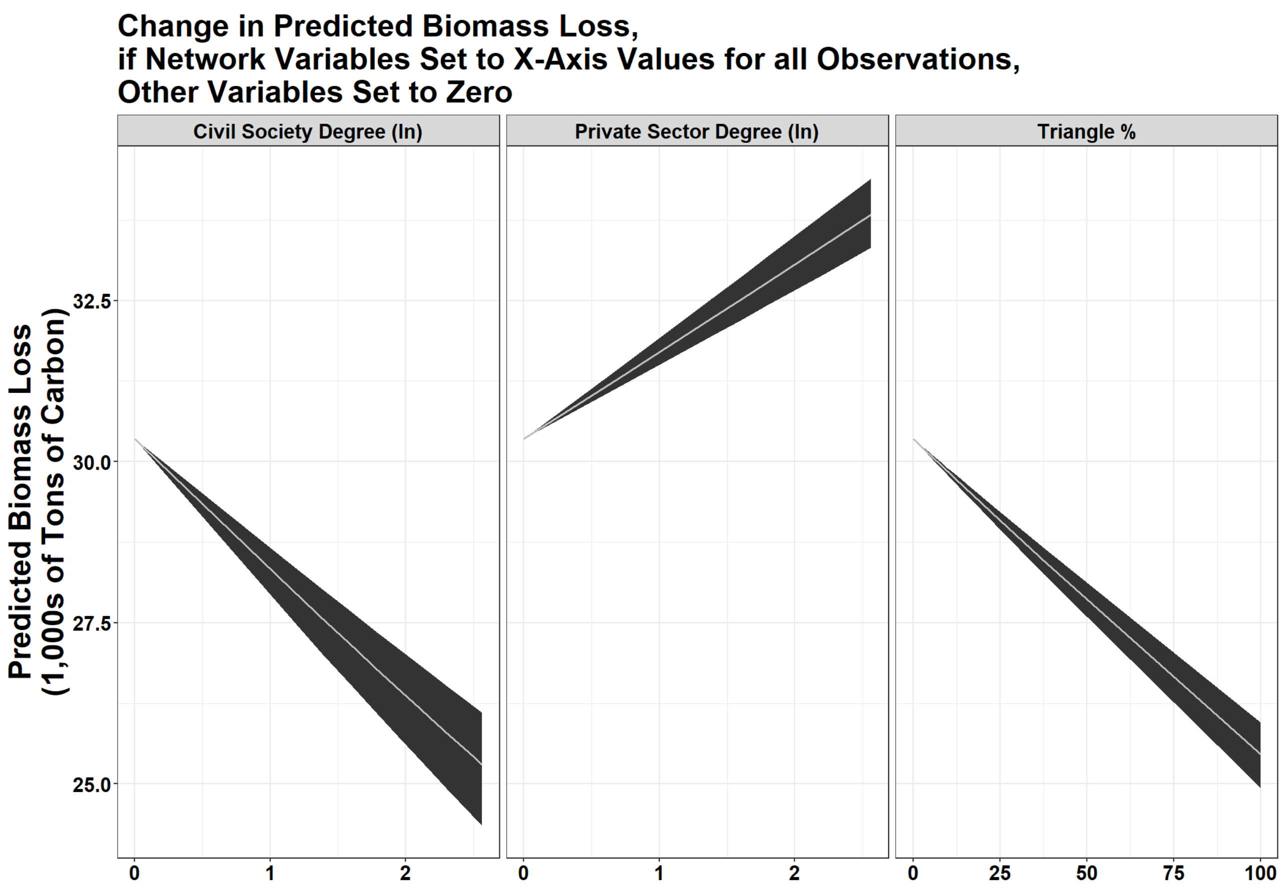

Figure 9. 99% confidence intervals for predicted biomass loss if all observations were set to the value of the independent network variable on the x-axis, calculated using the model with FSC, all network variables, and controls. All other variables we set to zero. Survival rates and confidence intervals calculated using the coxsimLinear function in the simPH package (Gandrud, 2015).

Summary of findings

Despite growing interest in both the impacts of forest certification and the role of networks in effective natural resource management, there is little literature that brings these two lines of inquiry together. Combining longitudinal remote sensing and governance network data, we estimated Cox proportional hazard models predicting the hazard of forest loss within 100-square meter forest plots in areas that eventually came under Forest Stewardship Council certification. We find substantial reductions in forest loss following Forest Stewardship Council-certification onset, with increases in village connections to civil society organizations, decreases in village connections with private sector organizations, and increases in bonding measured as the percent of closed triangles in the villages' ego networks. While a tentative initial intervention in a potentially expansive field of research, we believe our analysis highlights the benefits of this type of study for supporting efforts to sustainably manage forests.

The kind of analysis we undertook was only possible as a result of combining data on the evolution of governance networks with detailed evidence on land-cover change and resource use. In this paper, we sat out to investigate how bonding and bridging affect deforestation rates in Forest Stewardship Council-certified, community-managed forests. Our Cox proportional hazard models revealed Forest Stewardship Council certification contributed to substantial reduction in deforestation hazards, despite the fact that Forest Stewardship Council is not explicitly designed simply to reduce deforestation rates. This is consistent with other studies from the area using different data referenced in our above discussion of the empirical context.

Moving beyond previous Forest Stewardship Council impact assessments, however, we also found that improved network structure, in the form of increased bridging to civil society actors and bonding within the network, can supplement Forest Stewardship Council certification's impacts. Network structures appear to account for some of the variation in forest loss that might be attributed to Forest Stewardship Council certification if network variables were not explicitly modelled, but, more importantly, we also find that network structures' relationship with forest loss is substantial and distinct from certification effects. Bridging and bonding both mattered for forest loss, but, importantly, we find that bridging may either dampen or amplify deforestation, depending on the type of organizational partner to which bridges connect. While ties to civil society organizations tend to reduce hazards, ties to private sector organizations increase them.

Discussion

The evidence we present that cross-sectoral network connections may have heterogeneous effects is consistent with some previous literature. Lund, et al. (2015), for example, study two villages in Tanzania that took divergent forest management paths after their Village Land Forest Reserves were established, allowing divergent local priorities to more directly affect their forests. Rasolofson, et al. (2015), examining community-based forest management in Madagascar, find no difference between matched managed and unmanaged areas a whole, but substantial differences between areas that do and do not allow commercial exploitation.

These previous empirical findings are also consistent with literature addressing the politics of brokerage. Bixler, et al. (2016), for example, suggest it can be a double-edged sword, sometimes permitting powerful actors to "capture" the governance mechanism, undermining knowledge claims and turning policy toward their interests. Bartholdson and Porro (2018) argue community members may try to enlist different brokers to gain leverage in resource struggles. External actors' divergent interests might affect forest managers' calculus about the costs and benefits of different forest extraction strategies. Our finding also suggests that while some village ties to private sector organizations take place in the context of conservation projects, villages with many such connections may also be more strongly linked to external markets and face stronger incentives for forest extraction.

Conversely, bridging to civil society actors may indicate stronger coupling among social movement organizations interested in conservation, exerting normative pressure on villages to harvest more slowly or carefully. As seen in Figure 4, the vast majority of triangles in villages' ego networks include civil society organizations. Thus, increased triangle percentages might be measuring not only trust and social cohesion in general, but coordination among civil society actors in particular. When a higher percentage of village ties are embedded in closed triangles this could, if the triangles include diverse actors, also indicate that actors with diversified organizational interests are more likely to engage in practices that increase compliance, such as mutual monitoring.

Finding that both Forest Stewardship Council certification and the improved governance networks that often go along with its facilitation both have discernable impacts on forest loss is also important from a policy perspective. On the one hand, it suggests that investments to lower the transaction costs of governance network construction, perhaps through supporting network orchestrators like MCDI (Henriksen et al., 2018) or providing workshops and other opportunities for actors from different sectors to engage with one another (Henriksen et al., 2018), could be a relatively inexpensive complement to Forest Stewardship Council certification's role in climate change mitigation. Furthermore, because governance network improvement can take place without the formalization and start-up costs required by mechanisms like sustainability certification, this tool might be more feasible to apply across a wider spatial extent.

An important contribution of our study has been to link remote-sensing data on landscape geography and forest dynamics to village-level ego network structure before and after the onset of certification. While our study found a strong association between institutions and patterns of network embeddedness on the one hand and deforestation on the other, these results should be read against several important limitations which future research should aim to address.

First, our data set contained just four villages observed over a twenty-year period. While we had sufficient variation across villages and observation periods to estimate simpler bridging and bonding dynamics, more observations would be required to consider additional network complexity, such as assortativity, the tendency of similar types of organizations to form ties, or to estimate interactions between institutions and networks to better understand if and how institutional effects change conditional on network structure or vice-versa.

Second, we have focused exclusively on village ego networks, and we lack sufficient observations to estimate effects of network structure as a whole on environmental outcomes. Focal conservation actors such as the MCDI, for instance, orchestrate network formation at the district level with effects that might impact even non-Village Land Forest Reserve villages in different ways, depending on their embeddedness in the overall governance network. Conducting a multi-level network analysis (e.g. Wang et al. 2013) where local village ego networks are embedded in broader governance networks might provide a way of considering the broader resource bases that enable sustainable forest management. How local village elites interact with district level elite, for instance, could be an important factor in driving who benefits from institutions - and knowing where villages are located in such networks could be a way to address questions of power and inequality.

Third, our study has exclusively analyzed networks for villages and forest areas that have gone through a certification process, comparing landscape change before and after changes in institutions and networks. We did not include other forms of forest management institutions such as Tanzania's National Forest Reserves, which, because they are managed under state mandates, are likely to display fundamentally different ego network structures. Also, as it would potentially involve problematic selection biases, undermining our model identification strategy, we did not compare deforestation in our study areas to open-access areas that were never subjected to forest management regimes. More complex comparisons between different kinds of forest governance institutions and open-access areas that could serve as control sites might allow future researchers to disentangle selection dynamics from treatment in a more rigorous manner than we have achieved with our panel data. An idea would be to apply matching techniques based on landscape characteristics, allowing for more rigorous comparisons to mitigate selection bias resulting from non-random distribution of different governance systems. Accounting for such dynamics would also provide a better estimation strategy to identify the direct impact of networks on how communities modify their forest landscapes.

Fourth, our study follows the standard conservation approach to understanding deforestation, in that we focus on plots that were initially forest to track what drives the risks of forest resource extraction. If our only concern were maintaining as much standing forest as possible this approach might be sufficient. From a carbon storage perspective, however, it would be important to consider not only deforestation but also forest growth and regrowth, particularly in mosaic swidden landscapes like the one we study. Further, considering forest plots as individual observations fails to include broader landscape dynamics and the fact that treecover is not intrinsically environmentally beneficial independent of context (Henriksen, 2015). A more deeply relational perspective on landscape ecology would consider not only individuals and institutions to be embedded in networks but also particular natural objects as embedded in broader networked landscapes where flora and fauna coexist (Sayles, et al., 2019). Understanding the connectivity of forest plots in the broader landscape, for instance, could help identify forest plots more critical to landscape connectivity, keystone species habitat, and so on.

Conclusion

The voluminous literature on forest certification and network governance investigates two potentially complementary methods to simultaneously support forest conservation and livelihoods. Our analysis here indicates that bringing these discussions together may be quite fruitful. Our analyses indicate that embeddedness in both Forest Stewardship Council institutions and network structures is mutually supportive in protecting forests. In the previous section, we noted numerous ways in which this kind of research might be extended, for example by improving methods and data sources or by addressing these questions in other domains of natural resource management. Studies like these will likely be very beneficial in pushing the current literature on network governance of natural resource management to test hypotheses about how institutions and network structures affect on-the-ground environmental and livelihoods performance.

Appendix

Land-Cover Classification

As explained in the methods section, we used supervised random forest classification, trained using Google Earth Engine, to generate our land-cover data. Following a standard classification system (Food and Agriculture Organization of the United Nations, 2012), we used our algorithms to classify seven distinct forms of land cover (barren, cropland, human settlement, grassland, woodland, coastal forest, and water). While the two forest types (woodland and coastal) are ecologically distinct, we combined them into a single forest class for the purpose of analysis.

To train and assess the accuracy of our land-cover rasters, we collected ground-truthing points using Etrex, a Garmin 64s GPS, and a Samsung tablet with Locus Map. To augment these points, we also used georeferenced Topo sheets and very high resolution Google Earth imagery covering the study area (Klinkenberg, 2019). From these data, we generated training and validation samples of 4500 points, 2000 of which were forest cover. We randomly assigned 60% of our 4500 human-coded points for training and validation, reserving the remaining 40% as a test dataset. To be clear, the validation and test datasets were kept separate and consistent for all runs of the machine-learning algorithms described below.

We used our training points to classify land cover for the study area in 2000, 2004, 2009, 2014 and 2018 at a 10-meter resolution based on annual composite imagery from Sentinel-2, Sentinel-1, Landsat-8, Landsat-7 and Landsat-5, collected with Google Earth Engine (https://code.earthengine.google.com/). These images have been found to be quite useful in detecting forest and various forms of non-forest land cover over time (Chander, et al., 2009; Haeusler, et al., 2017; Rüetschi, et al., 2019). Once collected, we applied standard radiometric and atmospheric error corrections to the images (Japan Association of Remote Sensing, 1999; Turks, 1990). To improve classification accuracy, we used Google Earth Engine to compute natural digital vegetation index, enhanced vegetation index, normalized difference water index, normalized difference built-up index, a digital elevation model (Farr, et al., 2007), ratio (3:5-4:6), ratio (5:4-6:5), ratio (2:11), Sentinel-1 values (Green, et al., 1998; Xue & Su, 2017).

Again in Google Earth Engine, we deployed a random forest classifier due to its ability to produce accurate classification results for multiple research objectives, manage thousands of input variables without variable deletion, and produce internally unbiased estimates (Pal, 2005). As no classification is error-free (UTSA, 2017), it is important to assess classification accuracy prior to using remotely sensed data by comparing classifications to ground-truthed data. Following Gallego (2004), we used a confusion matrix, which compares the agreement between pixel classifications and ground-truthed land cover. Using our validation sample, we found that overall accuracy for all classified images averaged 89.7%, with a Kappa coefficient above 0.94. We present the confusion matrices for each year in Tables A1 through A3.

	Bare Land	Built Up Area	Cropland	Coastal Forest	Grassland	Water	Other Forest	Total	User accuracy
Bare Land	136	7	7	0	6	2	2	160	0.85
Built Up Area	11	169	7	0	13	0	0	200	0.85
Cropland	9	6	293	1	8	2	1	320	0.92
Forest	0	1	3	373	4	0	19	400	0.93
Grassland	12	3	6	0	132	7	0	160	0.83
Water	3	0	6	0	7	143	1	160	0.89
Woodland	0	1	5	12	4	1	377	400	0.94
Total	171	187	327	386	174	155	400	1800	
Producer accuracy	0.80	0.90	0.90	0.97	0.76	0.92	0.94		

Table A1. Confusion matrix for 2000 land-cover raster, computed on 40% of the sample point reserved for validation. Kappa = 0.95; Overall Accuracy = 90%

	Bare Land	Built Up Area	Cropland	Coastal Forest	Grassland	Water	Other Forest	Total	User accuracy
Bare Land	127	12	9	0	10	2	0	160	0.79
Built Up Area	14	164	11	0	11	0	0	200	0.82
Cropland	12	8	286	2	7	2	3	320	0.89
Forest	0	3	7	366	9	0	15	400	0.92
Grassland	10	8	11	0	125	4	2	160	0.78
Water	3	0	2	0	17	136	2	160	0.85
Woodland	2	1	5	12	6	4	370	400	0.93
Total	168	196	331	380	185	148	392	1800	
Producer accuracy	0.76	-0.84	0.86	0.96	0.68	0.92	0.94		

Table A2. Confusion matrix for 2009 satellite images, computed on 40% of the sample point reserved for validation. Kappa = 0.95; Overall Accuracy = 87%

	Bare Land	Built Up Area	Cropland	Coastal Forest	Grassland	Water	Other Forest	Total	User accuracy
Bare Land	143	6	5	0	6	0	0	143	6
Built Up Area	16	166	8	0	10	0	0	16	166
Cropland	7	4	301	1	5	0	2	7	4
Forest	0	0	3	381	3	0	13	0	0
Grassland	7	5	8	0	139	1	0	7	5
Water	0	0	2	0	9	149	0	0	0
Woodland	0	0	4	9	2	0	385	0	0
Total	173	181	331	391	174	150	400	173	181
Producer accuracy	0.83	0.92	0.91	0.97	0.80	0.99	0.96	0.83	0.92

Table A3. Confusion matrix for 2018 satellite images, computed on 40% of the sample point reserved for validation. Kappa = 0.94; Overall Accuracy = 92%

We created both dependent and independent variables from our classified land-cover datasets. To create our dependent variable, we used the raster (Hijmans, 2020) package in R 3.6.2 (R Core Team, 2019) to identify all pixels that were forested in 2000, tracking these forest plots through subsequent observation years to identify if and when their land cover changed to something other than forest.

Inferential analysis

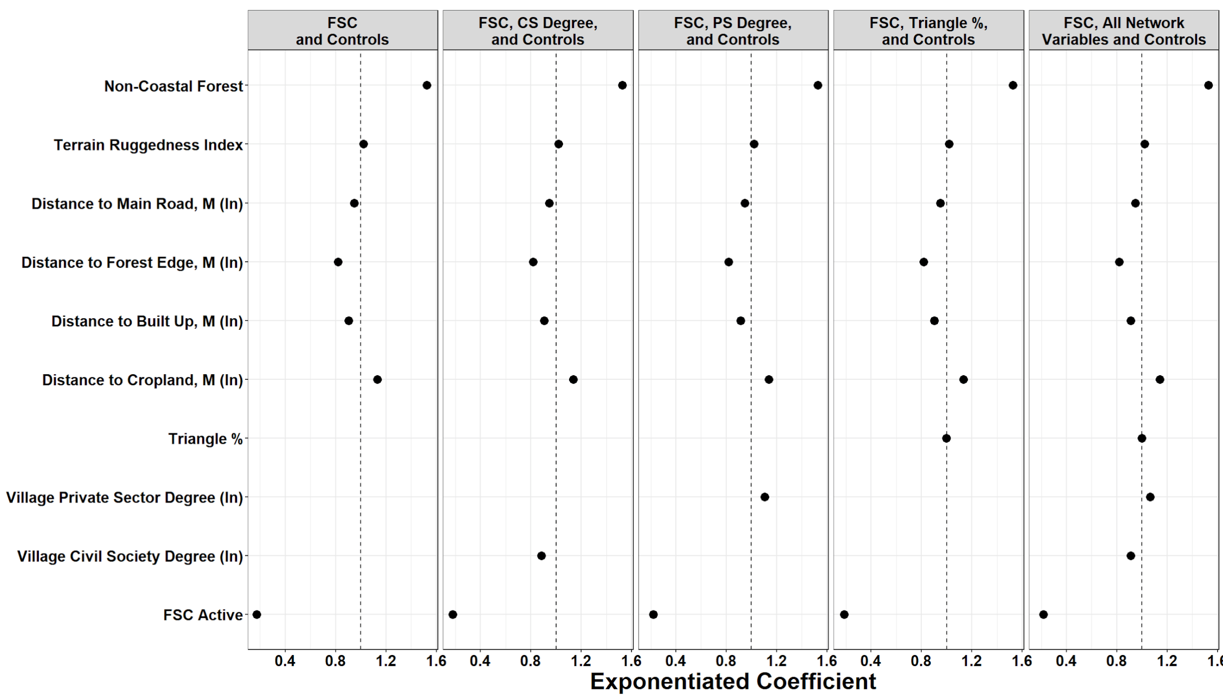

Figure A1. Estimated coefficients for all variables for models presented in Figure 7. The figure includes 99% credible intervals, but the points used to designate the median coefficient estimate are in all cases larger than the credible intervals.

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