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Between socio-economic drivers and policy response: spatial and temporal patterns of tree cover change in Nepal

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Despite the local and global importance of forests, deforestation driven by various socio-economic and biophysical factors continues in many countries. In Nepal, in response to massive deforestation, the community forestry program has been implemented to reduce deforestation and support livelihoods. After four decades of its inception, the effectiveness of this program on forest cover change remains mostly unknown. This study analyses the spatial and temporal patterns of tree cover change along with a few socio-economic drivers of tree cover change to examine the effectiveness of the community forestry program for conserving forests or in reducing deforestation. We also investigate the socio-economic factors and policy responses as manifested through the community forestry program responsible for the tree cover change at the district level. The total tree cover area in the year 2000 in Nepal was ~ 4,746,000 hectares, and our analysis reveals that between 2001 and 2016, Nepal has lost ~46,000 ha and gained ~12,300 ha of areas covered by trees with a substantial spatial and temporal variations. After accounting socio-economic drivers of forest cover change, our analysis showed that districts with the larger number of community forests had a minimum loss in tree cover, while districts with higher proportion of vegetation covered by community forests had a maximum gain in tree cover. This indicates a positive contribution of the community forestry program to reducing deforestation and increasing tree cover.

1 **Between socio-economic drivers and policy response: Spatial and temporal patterns of tree**
2 **cover change in Nepal**

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4

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11

12 **Abstract**

13 Despite the local and global importance of forests, deforestation driven by various socio-economic
14 and biophysical factors continues in many countries. In Nepal, in response to massive
15 deforestation, the community forestry program has been implemented to reduce deforestation and
16 support livelihoods. After four decades of its inception, the effectiveness of this program on forest
17 cover change remains mostly unknown. This study analyses the spatial and temporal patterns of
18 tree cover change along with a few socio-economic drivers of tree cover change to examine the
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20 deforestation. We also investigate the socio-economic factors and policy responses as manifested
21 through the community forestry program responsible for the tree cover change at the district level.
22 The total tree cover area in the year 2000 in Nepal was ~ 4,746,000 hectares, and our analysis
23 reveals that between 2001 and 2016, Nepal has lost ~46,000 ha and gained ~12,300 ha of areas
24 covered by trees with a substantial spatial and temporal variations. After accounting socio-
25 economic drivers of forest cover change, our analysis showed that districts with the larger number
26 of community forests had a minimum loss in tree cover, while districts with higher proportion of
27 vegetation covered by community forests had a maximum gain in tree cover. This indicates a
28 positive contribution of the community forestry program to reducing deforestation and increasing
29 tree cover.

30

31 **Introduction**

32 Forests play multiple roles in climate regulation, protection from extreme events, water filtration,
33 carbon sequestration, and biodiversity habitat apart from providing provisioning ecosystem
34 services such as food, timber, and medicines (Lambrechts et al., 2009; Anderegg et al., 2013).

35 Forests regulate regional and global climate through evapotranspiration, which in turn affects the
36 precipitation regime and the water cycle (Chagnon and Bras, 2005). About 45% of carbon found
37 in terrestrial ecosystems is stored in forests, and forests sequester more than 25% of annual
38 anthropogenic carbon emissions from the atmosphere (Pan et al., 2011). Forests, with the majority
39 of the world's terrestrial species of plants, animals, and microorganisms, are also one of the richest
40 biological areas on Earth (Lindenmayer et al., 2000). Furthermore, about 1.3 billion people,
41 primarily in developing countries, rely on forests for their subsistence livelihoods and a significant
42 part of cash income (Wasiq and Ahmad, 2004).

43

44 Despite the important and critical role forests' play in maintaining essential functions of our planet
45 and in human welfare, the process of converting forested land to other land uses such as cropland,
46 pasture, mining, and urban areas is persistent (Keenan et al., 2015). Although the rate of
47 deforestation has slowed down in recent years, it is still alarmingly high (FAO, 2010). About 13
48 million hectares (ha) of forests were lost annually from 2010 to 2015 at the global scale, and the
49 extent of forest loss is higher in tropical countries (Hansen et al., 2013; FAO, 2015), where
50 biological diversity as well as reliance on forests for subsistence level livelihoods, are the highest.
51 Deforestation has caused degradation of quality and amount of ecosystem services around the
52 world reducing biodiversity, undermining the flood retention capacity and soil stability as well as
53 producing negative impacts on local livelihoods and regional economies (Wagner et al., 2015).
54 The global deforestation is causing a significant amount of carbon emission (8-10% of total)
55 contributing to global climate change and environmental degradation affecting human wellbeing
56 (Le Quéré, 2016; Lambrechts et al., 2009). Therefore, efforts for accurate monitoring of forests at

57 different scales have received particular attention in recent years (FAO, 2015; Shimada et al.,
58 2014).

59

60

61

62 *Forest cover change and its drivers*

63 Deforestation is influenced by a wide range of factors such as agricultural expansion, insecure land
64 tenure, international markets, colonization, infrastructure and road building, urbanization, mining,
65 grazing, uncontrolled fire, political unrest, fuelwood extraction, and timber logging (Angelsen and
66 Kaimowitz, 1999; Geist and Lambin, 2002; Rudel et al., 2009; Ferretti-Gallon and Busch, 2014).

67 Various demographic, socioeconomic, biophysical, political, cultural, and technological drivers,
68 acting individually or synergistically, stimulate the anthropogenic activities of the agents (i.e.,
69 small farmers, ranchers, plantations, loggers) causing deforestation or forest degradation

70 (Angelsen and Kaimowitz, 1999; Kissinger et al., 2012). For example, increase in human
71 population requires more land for food, space, and other commodities resulting in the conversion
72 of forest areas into agriculture or other land uses (Kanninen et al., 2007). A synthesis of more than

73 140 economic models analyzing the causes of tropical deforestation showed that more roads,
74 higher agricultural prices, lower wages and a shortage of off-farm employment lead to more
75 deforestation, while the effect of technical change, agricultural input prices, household income

76 levels and tenure security on deforestation is unknown, and the role of macroeconomic factors
77 such as population growth, poverty reduction, national income, economic growth, and foreign debt
78 on deforestation is ambiguous (Angelsen and Kaimowitz, 1999). However, the drivers of

79 deforestation vary across geographical locations and historical contexts; over the last 50 years, the

80 agents of deforestation have changed (Laurance and Balmford, 2013). Historically, forests were
81 cleared for crops or livestock, and small farmers were considered as a major driver of deforestation.
82 Conversely, after economic globalization since 1990, forests have been cleared for massive
83 agricultural expansion, road building, wood extraction, and infrastructure development (Rudel et
84 al., 2009; Laurance and Balmford, 2013). A large-scale agriculture expansion for cattle ranching,
85 soybean and palm oil production, and timber logging is causing deforestation in many countries
86 such as Brazil and Indonesia (Brown et al., 2005; Morton et al., 2006; Arima et al., 2011).

87

88 Various approaches were adopted globally such as the establishment of protected areas, forest
89 restoration, protection and afforestation activities, and provision of economic incentives to reduce
90 and prevent deforestation or forest degradation (Brooks et al., 2012; Le Saout et al., 2013). Around
91 15.4% of the world's land area (Deguignet et al., 2014) and about 24% of the total area of Nepal
92 are covered by protected areas (GoN, 2014b), which have contributed to reducing deforestation
93 and conserving forests. As an alternative to strict protection, as practiced in protected areas,
94 community-based conservation initiatives such as community forestry program adopted in Nepal
95 and other developing countries also plays a successful role in forest protection (Brooks et al., 2012;
96 Porter-Bolland et al., 2012). More recently, reforestation has been a global phenomenon, and many
97 developing countries have undergone through a forest transition—a shift from net loss to a net
98 increase of forest cover (Meyfroidt and Lambin, 2011). During 1990-2015, a net loss of the forest
99 area has been slowing down and afforestation has increased at a global scale primarily in 13
100 tropical countries, forest transition has undergone since 1990 (Sloan and Sayer, 2015). Forest
101 transitions result from various trends such as natural regeneration of forests, forest plantation, and
102 adoption of agroforestry (Meyfroidt and Lambin, 2011). Migration of farmers from rural areas to

103 urban centres and economic shift from agriculture to industry and services stimulate forest
104 recovery and gain (Aide and Grau, 2004). In the context of South Asia including Nepal,
105 reforestation and regrowth of forest are attributed to human drivers particularly to the devolution
106 of forest management to local communities in the form of community forestry (Nagendra, 2009).
107

108 Globally, community forest management (CFM) has been considered a promising approach to
109 sustainable forest management over the past few decades (Arnold, 2001). Although CFM has
110 various definitions and interpretations, CFM is a government-approved form of forest management
111 in which the rights, responsibilities, and authority for forest management rest, at least in part, with
112 local communities (Newton et al., 2015). The primary aim of CFM is maintaining ecological
113 sustainability (reduce deforestation, preserve biodiversity) while improving livelihoods of the
114 local community (Bowler et al., 2012). Despite some examples of CFM failures (Tole, 2010;
115 Bowler et al., 2012), in many countries, it has produced successful outcomes such as improvement
116 of forest cover, increase in plantation zones, equity of benefit sharing, or reduction of community
117 poverty (Pagdee et al., 2006). In some tropical countries, the community managed forest plays
118 more important role in maintaining forest cover than protected areas; community forestry has
119 lower deforestation rates than protected areas do (Porter-Bolland et al., 2012). Despite these mixed
120 outcomes, CFM is the widespread approach to forest management in developing countries
121 including Nepal. In the context of climate change, CFM is now viewed as an option to reduce
122 greenhouse gas emission through REDD+ (Reducing Emissions from Deforestation and Forest
123 Degradation), a global climate change mitigation mechanism, which has been under negotiation
124 by the United Nations Framework Convention on Climate Change (UNFCCC) (Agrawal and
125 Angelson, 2009).

126

127 Nepal has a promising history of forest management and shows an excellent example of
128 community-based forest conservation globally although the country has only 5.96 million hectares
129 forests (40.36% of the country's land area). Concerned with massive deforestation and forest
130 degradation in the early 1970s, Nepal initiated one of the most extensive community forestry (CF)
131 programs in the world by handing government-controlled forests over to community forestry users
132 groups (CFUGs) formed by local communities through an enactment of the Panchayat Forest Rules
133 (Acharya, 2002). Since then about 1.8 million ha of the forest areas have been handed over to and
134 managed by, 19,361 CFUGs (approximately 1.45 million households or 35% of Nepal's
135 population) under community-based forest management program (DoF, 2015). The community
136 forests provide various ecosystem goods and services to the local communities and help to global
137 communities by sequestering a significant amount of carbon. Nepal has recently jointed to the
138 United Nations collaborative initiative on REDD+ program—one of the leading global efforts to
139 reduce deforestation to mitigate climate change, prepared a Readiness Preparation Proposal (R-
140 PP) and formed REDD+ institutional framework (MoFSC, 2012; UN-REDD, 2014). Finally,
141 under the most recent United Nations Framework Convention on Climate Change (UNFCCC)
142 agreement in Paris to reduce emissions, Nepal's Intended Nationally Determined Contributions
143 (INDCs) to emissions assign a vital role to forests. Nepal aims to enhance forest carbon stock by
144 5% by 2025 as compared to 2015 levels and decrease mean annual deforestation rates by 0.05%
145 from 0.44% (DFRS, 2015).

146

147 Nepal does not have a long-recorded history of deforestation or forest cover change. The initiation
148 of large-scale monitoring of forest cover change occurred only after 1960 although deforestation

149 has been a major issue in Nepal. From 1964 to 1994, about 2.1 million ha of forests were converted
150 to shrubland or other land uses (Acharya et al., 2015). FAO data showed that the annual loss of
151 forest in the period between 2000 and 2005 was 1.39%, which remained stable during 2005-2010
152 (FAO, 2010). However, forest cover change at the national level has not been assessed in Nepal
153 after the second National Forest Inventory in 1999; therefore, there is no critical information
154 available about forest cover change at the national level in Nepal in recent years (DFRS, 2015).
155 Most of the recent studies on forest cover change were conducted in small areas (Uddin et al.,
156 2015a; Uddin et al., 2015b; Niraula et al., 2013; Poudel et al., 2015). Some recent studies have
157 outlined both drivers and underlying causes of deforestation and forest degradation in Nepal. A
158 total of nine major drivers of deforestation and forest degradation: i) forest fire, ii) overgrazing,
159 iii) unsustainable utilization of forest products, (iv) weak forest management practices, (v)
160 infrastructure development, (vi) urbanization and resettlement, (vii) encroachment, (viii) invasive
161 species, (ix) mining were identified (REDD Implementation Center, 2013). Likewise, population
162 distribution, migration, poverty, high dependency in forest products, insecure forest tenure are
163 major underlying causes of deforestation and forest degradation in Nepal (Acharya et al., 2015).
164 We use available data on the drivers and underlying causes of deforestation and analyse: a) the
165 spatial and temporal patterns of the tree cover change in Nepal from 2001-2014, b) the socio-
166 economic drivers of forest cover change, and c) the effectiveness of community forestry programs
167 on the tree cover dynamics. Our efforts mark the first attempt to analyse the tree cover change for
168 the entire country (albeit at the district level), relate this loss and gain to socio-economic drivers,
169 and identify policy-relevant interventions (community forestry) needed to stem deforestation and
170 forest conservation.
171

172 **Materials and Methods**

173 *Study area*

174 Nepal provides an excellent case study to understand the effectiveness of community-based
175 institutions on forest conservation as a significant portion of the forests of this country is managed
176 by local communities. The entire country, Nepal (figure 1) with a geographical area of 147,181
177 km², was divided into five physiographic zones—High Himal, High Mountain, Hill, Siwalik, and
178 Terai—based on climate, soil, elevation, topography, vegetation and forest types (LRMP, 1986).
179 Forest and agriculture sectors have the highest contributions to the national gross domestic product
180 (GDP), contributing 26.1% share of the total GDP of Nepal (CBS, 2015b). About 69% of the
181 employed population in Nepal is engaged in agriculture, forestry, and fishing (CBS, 2015a). The
182 country is politically divided into 75 districts; the district is the lowest spatial unit used here for
183 data analysis, as most of the demographic, socio-economic, and environmental data are available
184 only at the district level in Nepal. We believe that district-level analyses do not compromise data
185 availability and spatial accuracy.

186

187 *Tree cover data*

188 We used a subset of global tree cover data provided by global forest watch (Hansen et al., 2013,
189 updated every year). The global forest watch offers the highest resolution datasets (30m ground
190 resolution) of tree cover using Google Earth Engine and Landsat's satellite imagery for the entire
191 globe. The data show both the extent and change of tree cover globally (Hansen et al., 2013). We
192 called it tree cover, however; it is synonymously called forest cover. Unfortunately, there is no
193 shared definition of forests globally. Generally, forests are defined for specific purposes, based on
194 views, concepts, and priorities (Chazdon et al., 2016). Three common criteria: canopy cover,

195 intact-area, and the height of the trees are commonly used for defining forests, but these criteria
196 are not uniformly used by different agencies and countries. For example, Food and Agriculture
197 Organization of the United Nations (FAO) uses 5 m for the height of trees, 10% crown cover and
198 0.5 ha for minimum size of forest (Lambrechts et al., 2009) whereas United Nations Framework
199 Convention on Climate Change (UNFCCC) calls forests for area of 0.05-1 ha with 10-30% canopy
200 and >2-5m tall trees (Sasaki and Putz, 2009). These differences in definitions and methodologies
201 used to map and monitor forests often lead to differing results (Lambrechts et al., 2009).
202 Furthermore, the definition and assessment issues have handicapped the efforts to understand the
203 tree cover dynamics (Rudel et al., 2016). The definition of tree cover adopted for this study was
204 ‘all the vegetation area greater than 5 meters in height with the canopy cover of at least 30%’ as
205 used by Hansen et al. (2013) since we used Hansen’s data from the Global Forest Watch. We
206 disaggregated tree cover change (loss and gain) data for the 75 districts and five physiographic
207 zones of Nepal.

208

209 *Drivers of tree cover change and policy responses*

210 According to Angelsen and Kaimowitz (1999), the framework of deforestation should consider
211 five types of variables (the magnitude and location of deforestation as a dependent variable, the
212 agents of deforestation, the choice variables, agents’ decision parameters, the macroeconomic
213 variables, and policy instruments) in the models of deforestation. We selected a list of potential
214 factors of deforestation and forest degradation in the context of Nepal after carefully reviewing the
215 literature on global and local drivers of—and causes to—forest cover change, while also
216 considering the availability of data. We did not consider some factors associated with deforestation
217 and forest degradation identified by previous studies (Angelsen and Kaimowitz, 1999) as relevant

218 to Nepal. For example, some of the immediate causes of deforestation listed by Angelsen and
219 Kaimowitz (1999) such as agriculture prices, prices of agricultural inputs and credit and underlying
220 causes of deforestation such as timber prices, external debt, trade and structural adjustment may
221 be associated with deforestation in Nepal but the data is not available.

222

223 Data on various factors associated with deforestation and forest degradation such as demographic
224 (population, population density, migration), economic (number of poor people, poverty incidence,
225 poor people density, livestock number, livestock density), social (human development index,
226 fuelwood collection), and environmental (fire, road length, elevation, slope) along with the policy
227 response variables (number of community forest user groups and the share of the major vegetation
228 area covered by community forest) were gathered from various sources (Table 1). In the following
229 paragraphs, we provide our justification for selecting these factors.

230 The population is widely seen as an underlying driver of deforestation (Angelsen and Kaimowitz,
231 1999; Kissinger et al., 2012). In the natural resource-dependent country like Nepal, population
232 growth increases demand for natural resources primarily forests and requires more lands for
233 habitation. As the population grows, more people are living in the cities, and urbanization is
234 considered as one of the major drivers of deforestation in Nepal (REDD Implementation Center,
235 2013). A high unemployment rate coupled with population growth has accelerated both domestic
236 and international migrations in Nepal, and the country has emerged as a remittance-dependent
237 economy shaped by the earnings of labour migrants for foreign employment. Remittance
238 contributes around 29% to the Gross Domestic Product (GDP) of Nepal, making the nation top
239 third among the countries in terms of remittance contributions to GDP (World Bank, 2016).
240 Migration particularly labour migration, has resulted in land abandonment and the conversion of

241 agricultural land into other land use such as forests, shrubs or fallow in some areas (Paudel et al.,
242 2014). Therefore, total population, population density, and migration are considered as dependent
243 variables in our model. We used the most recent national population census as a demographic
244 variable (CBS, 2012). We also included the data on out-migration (the number of people migrated
245 abroad for employment as there is no data on internal migration available) (GoN, 2014a).

246

247 Human development index, which measures income, health, and education, is linked with
248 deforestation and hence incorporated in our model; countries with low HDI has a high rate of
249 deforestation and vice versa (Jha and Bawa, 2006). Although income and poverty are correlated,
250 poverty is a multidimensional social phenomenon (Anand and Sen, 1997). There is a high rate of
251 poverty in naturally forest-dense areas, and poverty is considered as an important underlying cause
252 of forest conversion by smallholders (Chakravarty et al., 2012). However, the linkage between
253 poverty and forest degradation is ambiguous (Angelsen and Kaimowitz, 1999) and the natural
254 resource degradation may depend on a complex range of choices and tradeoffs available to the
255 poor (Barbier, 2010). Nepal still has a large number of people living in poverty and has a low score
256 in HDI. Therefore, we accounted for HDI and poverty in our model. District wise figures of HDI,
257 number of poor people, and poverty incidence were obtained from the latest human development
258 report (NCP/UNDP, 2014).

259

260 Overgrazing is considered as one of the major drivers of forest loss and degradation in Nepal
261 (Acharya et al., 2015; REDD Implementation Center, 2013). Grazing in the forested areas and
262 stripping trees to provide fodder for animals are common in many parts of Nepal. Therefore, we
263 considered this as a variable to our model. The most recent data of livestock were acquired from

264 the statistical information on Nepalese Agriculture (GoN, 2012a). Since the populations of pig,
265 poultry, and fowl do not have a direct impact through grazing on forests, we excluded them from
266 the populations of cattle, buffalo, sheep, and goat and used as the livestock number. We calculated
267 the livestock ratio by dividing the livestock number with the extent of the major vegetation cover
268 of each district assuming the pressure of these livestock exerts mainly on vegetation. The
269 vegetation area (cumulative area of forests, shrubs, grasslands and sparse vegetation) for a district
270 was calculated by using a global land cover share map, version 1.0 (Latham et al., 2014).

271

272 Although fire can be a helpful tool for forest management, it can be a significant cause of
273 deforestation if abused (Chakravarty et al., 2012). Forest fire induced by humans is one of the key
274 drivers of forest degradation in Nepal (Matin et al., 2017). We gathered the district wise and
275 temporal data of forest fire from Martin et al. (2017). Their analysis is based on the active fire data
276 from MODIS satellites dating from 2003 to 2013.

277

278 Fuelwood gathering is considered as one of the causes of deforestation and forest degradation in
279 tropical areas (Chakravarty et al., 2012). In rural areas of Nepal, wood derived from natural forests
280 is one of the most critical sources of fuelwood (Christensen et al., 2009). Fuelwood contributes
281 about 70% of the total energy supply for the rural population of Nepal (Kandel et al., 2016).
282 Therefore, we included fuelwood gathering as a variable in our model. We collected district wise
283 data of the total number of households used fuelwood for cooking from the national population
284 and housing census (CBS, 2012).

285

286 Proximity to the roads affects forest condition; forests closer to roads in the distance are more
287 likely to be cleared (Liu et al., 1993; Lambin, 1997). In rural Nepal, there has been a prolific
288 growth of earthen road expansion in recent years. Due to the mountainous topography, steep
289 slopes, and weak soils, these poorly constructed rural roads have increased the probability of
290 landslides especially during the heavy monsoonal rainfall (Leibundgut et al., 2016). Therefore,
291 road buildings may have an impact on the condition of forests and we considered the length of the
292 road as a variable in our model. The data on road was collected from the Department of Roads,
293 Nepal (GoN, 2012b). We also used digital elevation data (DEM) from Shuttle Radar Topographic
294 Mission (SRTM) (<http://srtm.csi.cgiar.org/>) and calculated slope from DEM in ArcGIS to use in
295 our model.

296

297 We used the total number of CFUGs and the proportion of the vegetation area covered by
298 community forests in a district as a proxy to measure the effectiveness of community forestry
299 programs. The data on the number and area of CFUGs were obtained from the Management
300 Information System maintained by the Department of Forests, Nepal (DoF, 2015). To normalize
301 the non-forested area effect, the total area of community forests in a district was divided by the
302 major vegetation area of that district because the government handed over only the area covered
303 by potential vegetation (forests, grasslands, shrubs, and sparse vegetation areas) to the local
304 community as the community forests.

305

306 *Data analysis*

307 We analysed the net change (loss and gain) of tree cover for each district over a 15-year period
308 from 2001 to 2016. Because protected areas cover a significant area of Nepal (about 24% of the

309 total land area) and have a separate management system, the geographical areas covered by
310 protected areas were excluded in further analysis to determine the impacts of the drivers of
311 deforestation and effectiveness of the community forestry program on the gain and loss of tree
312 cover. We build two models; in the first model, the proportion of forest loss was used as a
313 dependent variable and in the second, proportion of forest gain. The demographic, economic,
314 social, and environmental variables were used as independent variables in both models. After
315 testing our data with the assumptions required for multiple linear regressions (heteroscedasticity,
316 normality, outliers, multicollinearity), we conducted the ordinary least square (OLS) regression
317 analysis to predict the impact of independent variables on the dependent variables. We examined
318 multicollinearity among predictor variables (Supplementary figure 1) and eliminated highly
319 correlated ($r > 0.75$) four variables resulting in 12 independent variables for the initial models. We
320 used stepwise model selection method on R software package to select the final model (R Core
321 Team, 2017). The initial models were evaluated by using Akaike Information Criteria (AIC), the
322 commonly applied criterion to compare models for the goodness of fit and the model with the
323 smallest AIC was chosen as the best-fit model (Burnham et al., 2004).

324

325 As the socio-economic data were available at the district level, we choose 75 districts as study
326 units. We conducted area-based correction for the dependent variables (tree cover loss and gain)
327 to normalize the effect of the district size. Rather than using total area of tree cover loss and gain,
328 we used proportions of forest that were lost or gained in the district as dependent variable in the
329 regression models.

330

331 We also quantified the spatial pattern of tree cover loss to observe the spatial association between
332 roads and the loss and gain of tree cover, using the GIS-based buffering approach, from one to
333 five-kilometre distance from the current road networks. We counted the total number of pixels of
334 tree cover loss and gain within a range from one to five kilometres from the roads and calculated
335 the total areas. Since we have temporal data of forest fire incidence and forest fire is considered a
336 major driver of deforestation and forest degradation in Nepal, we also compared annual trends of
337 tree cover loss with the trends of the forest fire.

338

339 We visually compared the tree cover loss data with the high-resolution images of the Google Earth
340 Pro. We first identified 132 larger patches of tree cover loss and randomly selected 50 patches by
341 overlaying 1 km² grids on the layer of tree cover loss. We visually compared the images captured
342 around 2001 with the images captured around 2016 in those loss patches using the Google Earth
343 Pro. About 71.7% time, the tree cover loss patches matched with actual loss of tree cover
344 (Supplementary figure 2).

345

346 **Results**

347 *Spatial pattern of forest cover change*

348 The total tree cover area in the year 2000 in Nepal was 4,746,000 hectares. Nepal has lost 46,000
349 ha and has gained 12,200 ha areas of tree cover over the last 15 years from 2001-2016. However,
350 a substantial spatial variation was observed among physiographic zones, and districts; maximum
351 loss of tree cover in Siwalik (28%, 13,000 ha) followed by Hill (26%, 12,100 ha) and Terai (22%,
352 9,900 ha), Middle mountain (21%, 98,00 ha) and High mountain (2%, 1,100 ha). Regarding tree

353 cover gain, the Hill region gained the highest area of 6,200 ha (51%) followed by Siwalik 3,000
354 ha (25%), Terai 2,100 ha (17%), Middle mountain 830 ha (7%), and High mountain 70 ha (1%).

355

356 A major loss in tree cover was observed in Kailali (6%, 2,270 ha), Dang (5%, 2,090 ha), Sarlahi
357 (4%, 1,730 ha), Rautahat (3%, 1,260 ha) and Nawalparasi (3%, 1,180 ha) districts whereas Kaski
358 (0.09%, 34 ha) and Bhaktapur (0.1%, 42 ha) lost comparatively a smaller area of tree (Figure 2).

359 In terms of gain in tree cover, Dang with 880 ha (7%) forest gain was at the top position followed
360 by Nawalparasi (7%, 830 ha), Tanahun (6%, 650 ha), Palpa (6%, 620 ha) and Kailali (5%, 600 ha)
361 districts while Manang (0.01%, 1 ha), Kaski (0.01%, 1 ha) and Darchula (0.01%, 1 ha) gained a
362 lesser forest area. The maximum loss and gain of tree cover were observed within the five-
363 kilometre distance from the roads; the area of forest cover loss and gain decreased as the distance
364 from the roads increased (Figure 3a).

365

366 *Temporal pattern of forest cover change*

367 Over 2001-2016, the maximum loss in tree cover (6,180 ha) occurred in the year 2009 and the
368 minimum (1,040 ha) in the year 2015 (Figure 3b). Likewise, in different physiographic regions,
369 the maximum loss of tree cover in Terai occurred in 2009, Siwalik in 2011, Hill in 2012, Middle
370 mountain and High mountain in 2009. A significant correlation was observed between the annual
371 incidence of the forest fire with the annual loss of tree cover ($r=0.60$, $P = 0.049$), the maximum
372 resemblance in the trends was found after 2008 (Figure 3c).

373

374 *Drivers of change in tree cover*

375 We observed the associations between policy response variables (proportion of the major
376 vegetation area covered by community forest and number of CFUGs) and the proportion of tree
377 cover loss and gain by incorporating the effects of demographic factors, economic, social, and
378 environmental factors. The predictor variables identified by the AIC criterion are: a proportion of
379 area covered by community forests, number of community forests, population, HDI, and number
380 of migrants for the tree cover loss model. Likewise, a proportion of area covered by community
381 forests, number of CFUGs, number of poor people, fuelwood, and fire were retained for tree cover
382 gain model (Table 2). According to our model, the proportion of tree cover loss in a district is
383 significant and negatively correlated with the number of community forests in the district
384 suggesting the districts with a higher number of community forests have a lower amount of forest
385 loss (Table 2). Similarly, population and number of migrants have significantly positive
386 association while HDI was significant, and negatively correlated with the tree cover loss.

387

388 Similarly, the area of tree cover gain was significant and positively associated with the proportion
389 of the major vegetation area covered by community forests demonstrating that districts with a
390 higher the proportion of community forests have a more significant area of tree cover gain.
391 Likewise, forest fire showed a significant and positive relationship with the tree cover gain.

392

393

394 **Discussion**

395 In this study, we disaggregated tree cover (both extent and change) into five physiographic zones
396 and 75 districts of Nepal to compare spatial patterns of tree cover gain and loss. We also observed
397 the temporal profile of the loss in tree cover at two scales, national and regional (physiographic
398 zones). Furthermore, this study identified the demographic, social, economic, and environmental

399 factors of tree cover change and measured the effectiveness of the community forestry program in
400 changing the dynamics of tree cover. Our results are highly relevant to address the socio-economic
401 drivers of tree-cover change as well as to witness the effectiveness of the community forestry
402 program of Nepal.

403

404 Our results on various degree of tree cover loss and gain at district level correspond with the
405 localized studies, which found decrease in forest cover in some areas (Uddin et al., 2015a; Uddin
406 et al., 2015b) as well as increase in forest cover in others (Niraula et al., 2013; Paudel et al., 2015).
407 However, loss of tree cover is more prominent than gain in Nepal at the national scale. This study
408 also confirms the widespread anticipation of the spatial pattern of forest cover change in various
409 physiographic zones; higher rate of deforestation and forest degradation in Siwalik and Terai and
410 the regeneration of forest in the Hill and Middle mountain region (GoN, 2014b). The Terai and
411 Siwalik regions comprise mainly tropical Sal and Mixed Broad-Leaved forest and Hill
412 encompasses Hill Sal forest, Schima-Castanopsis forest, Chir Pine and Chir Pine-Broad Leaved
413 forests whereas High Mountain region has temperate forests such as Cypress, Rhododendron,
414 Spruce, and Oak Forests (Barnekow Lillesø et al., 2005). From the commercial point of view, Terai
415 and Siwalik regions have forests with maximum market value and are hence highly prone to
416 commercial exploitation (Acharya et al., 2015). In contrast, Terai region has the lowest proportion
417 (7%) of community forests while Hill and mountain have 75% and 16% respectively (GoN, 2013).
418 The total incidence of forest-fire as a whole has a significant and negative impact on the forest,
419 and the relationship can be observed in the temporal pattern in which the annual incidences of
420 forest fire correspond with the annual loss in tree cover. Furthermore, forest-fire is also considered

421 a primary cause of forest disturbance of Nepal (DFRS, 2015) and about 452,000 ha of land areas
422 including forests were burned in Nepal from 2003 to 2012 (FAO, 2015).

423

424 Our results indicate that the community forestry program played a crucial role in reducing
425 deforestation (tree cover loss) and increasing the forest area (tree cover gain) at the district level.

426 The significant and negative association between the proportion of tree cover loss and the number
427 of community forest shows that districts with a higher number of community forests have lesser

428 areas of loss in tree cover. Similarly, the significant and positive association between the tree cover
429 gain and the percentage of community-forested area in the district indicates a higher proportion of

430 community forests in the districts has a greater gain in tree cover. Community forests combine a
431 mixture of plantation and natural forests, and in most cases, local communities protect the

432 community-owned forests allowing natural regeneration and growth (GoN, 2013). Nevertheless,
433 the tree cover data (Hansen et al., 2012) used here do not distinguish between trees in plantations

434 and natural forests. Therefore, it is not possible to differentiate between regenerating forests due
435 to plantations or from the natural forests. Our study validates the local level studies (Niraula et al.,

436 2013; Gautam et al., 2004; Gautam et al., 2002) and widespread perception that community
437 forestry has a positive impact on the forest cover change by reducing the loss and increasing the

438 gain in forest areas at the district level. Furthermore, an analysis of the CFGUs reports based on
439 the perception of the user groups at national level showed that 79% of the CFUGs reported an

440 overall increase in tree density in the community forests (GoN, 2013). However, there are other
441 factors that are statistically associated with the forest cover loss such as population; a higher

442 numbers of people and a larger the number of migrant workers in a district, greater the areas of
443 forest loss. The positive association between forest loss and population makes more sense as the

444 growing population increases demands for natural resources creating more pressure to forests. In
445 the rural regions of Nepal, the dependency of the local people on the natural resources particularly
446 on forests is very high. This result is consistent with Angelsen and Kaimowitz, 1999; Jha and
447 Bawa, 2006; Ernst et al., 2013; Khuc et al., 2018). Significant and negative association between
448 the tree cover loss and HDI values indicates the districts with higher levels of development has
449 lesser tree cover loss. Studies found that HDI as a crucial predictor of forest transition (Redo et al.,
450 2012) and a lower rate of deforestation (Jha and Bawa, 2006). Lack of development and economic
451 opportunities in the districts with low HDI may make people rely heavily on forest resources for
452 subsistence use (Angelsen et al., 2014; Belcher et al., 2015) that might lead to the extraction of
453 more forest resources causing deforestation and forest degradation.

454

455 Road length is another variable, which has contributed significantly to both forest loss and gain
456 suggesting that accessibility is a crucial factor for forest cover change (loss and gain) (Angelsen
457 et al., 1999; Nelson et al., 2001; Newman et al., 2014). Construction of the road might lead to the
458 cutting of trees and facilitate forest encroachment. Due to the steepness in the hilly areas,
459 construction of unplanned earthen roads triggers landslides causing loss of vegetation (Leibundgut
460 et al., 2016). Furthermore, roads were recently built in many rural villages of Nepal, and most of
461 the community forests are located near villages in Nepal. Therefore, spatial concomitance might
462 lead to a positive relationship between forest cover loss and road network. Despite the positive
463 correlation between temporal trends of the number of forest fire incidences and tree cover loss, we
464 also found a positive association between forest fire days and tree cover gain. The forest fire has
465 both positive and negative impacts; the fire not only destroys forests and increases deforestation,
466 but also facilitates germination, and helps the establishment of commercial timber species by

467 eliminating growth-inhibiting vine loads (Cochrane, 2003). More detail study is necessary to
468 understand the impacts of fire on tree cover change in Nepal as in this study, the unit of analysis
469 is district and the precise localities of forest fire and the tree cover gain in a district might be
470 different.

471

472 **Conclusion**

473 This study has compromised the spatial accuracy of the higher resolution of data with the
474 availability of data at some extends. An analysis at a finer spatial scale would have produced a
475 more nuanced view. Unfortunately, there is no spatial information (maps with boundary) available
476 for all the CFUGs in Nepal. Although the analysis at the village development committees (VDCs),
477 the lowest political unit of Nepal could provide more detail overview of tree cover change, the
478 information on socio-economic drivers is available only at a district level. Despite this shortcoming
479 due to limitations in data availability, our study has highlighted the different factors of
480 deforestation and the effectiveness of the major forest conservation policy in Nepal albeit at a
481 coarse scale. Because of these limitations, the inference of a robust causal relationship between
482 the dependent and independent variables is rather difficult. Globally, the data of tree cover loss
483 provided by Hansen et al. (2013) was correct only 75% of the time (Weisse and Petersen, 2015)
484 and the data do not differentiate temporary and permanent loss of tree cover between natural forests
485 or tree plantations (Harris et al., 2016). The quality of socio-economic data of developing countries
486 is often criticized (Meyfroidt and Lambin, 2008). Given our limited understanding of the forest
487 cover change in Nepal, the results of this study are useful in formulating policies and programs to
488 address the drivers of deforestation and persistently improve the existing policy on community
489 forestry. We hope that future research with a higher resolution of demographic and socio-economic

490 data (at the scale of community forest) can provide more nuanced results and may identify
491 additional factors associated with forest cover change in Nepal.

492

493 Despite some shortcomings due to limitations in data availability and quality, this paper analyses
494 the spatial and temporal patterns of tree cover loss and gain in the light of socio-economic drivers
495 and effectiveness of one of the major forest conservation policies of Nepal. This study addresses
496 a long-term standing policy question regarding the effectiveness of community forestry programs
497 and reveals the likely socio-economic drivers of tree cover change in Nepal. Our results confirm
498 that both the extent of community forestry and the number of CFUGs have positive impacts on the
499 forests. Districts with a higher number of community forests have a minimum loss in tree cover,
500 and the districts with a higher percentage of community forest area have a maximum gain in tree
501 cover. Although the community forestry program has a positive impact on the forest cover by
502 reducing the forest loss and increasing the gain, the other drivers of forest loss have been leading
503 to the overall decline in forest area in Nepal. Nepal lost almost 46,000 ha forest area while Nepal
504 gained roughly 12,300 ha over 2001-2016. Therefore, in order to conserve forest areas in Nepal,
505 the current policy can be continued and improved if necessary, coupled with addressing the
506 underlying cause of deforestation.

507

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Table 1 (on next page)

Description of the variables used in the model

Table 1. Description of the variables used in the study

Variables	Description	Unit	Data source
Ncfug	Number of community forestry user groups (CFUGs). CFUG is a community based local institution that has right to manage and govern community forests in Nepal's community forestry program.	Number	Community Forestry National Database Department of Forest, Government of Nepal (DoF, 2015) http://dof.gov.np/image/data/Community%20Forestry/Detail%20FUG%20All.pdf
Rcfug	Percentage of major vegetation area (cumulative of trees, grasslands, shrubs and sparse vegetation areas potential to be community forests) in the district covered by community forests.	Percentage	Calculated based on the land cover map and area of community forest in the district
P2011	Total population in 2011 based on population census.	Number	Central Bureau of Statistics, Government of Nepal (CBS, 2012) http://cbs.gov.np/image/data/Population/District%20Level%20Detail%20Report/Household_Tables.pdf
Pdensity	Population density in 2011 (calculated by dividing population	Number/km ²	Central Bureau of Statistics (CBS),

with the area of a district outside the protected areas)

Government of Nepal (CBS, 2012)

http://cbs.gov.np/image/data/Population/District%20Level%20Detail%20Report/Household_Tables.pdf

Pincid	Poverty incidence (Headcount index value). Poverty incidence is share of population having an income or consumption below the poverty line.	Percentage	National Planning Commission, Government of Nepal (NPC/UNDP, 2014)
			http://www.hdr.undp.org/sites/default/files/nepal_nhdr_2014-final.pdf
Ppop	Absolute number of poor people under poverty threshold.	Number	National Planning Commission, Government of Nepal (NPC/UNDP, 2014)
			http://www.hdr.undp.org/sites/default/files/nepal_nhdr_2014-final.pdf
Ppopdensity	Density of poor people (calculated by dividing population of absolute number of poor people with the area of a district	Number/km ²	Calculated here

outside the protected areas)

Livest	Total number of livestock (sum of total cattle, buffalo, sheep and goat)	Number	Promotion and Statistics Division, Ministry of Agricultural Development, Government of Nepal (GoN, 2012a) http://www.moad.gov.np/en/publication?PublicationSearch%5Bcategory_id%5D=13&PublicationSearch%5Btitle%5D=&PublicationSearch%5Badded_date%5D=
Rlivest	Ratio of total number of livestock with the extent of the major vegetation area in a district	Number/km ²	Calculated here
Hdi	Human development index (Composite index of life expectancy, education and per capita income)		National Planning Commission, Government of Nepal (NPC/UNDP, 2014) http://www.hdr.undp.org/sites/default/files/nepal_nhdr_2014-final.pdf
Rlength	Total length of roads	Km/100km	Department of Roads, Government of Nepal (GoN, 2012b) http://dor.gov.np/home/page/road-statics-

Fire	Total number of fire incidence from 2001 to 2013	Number	<p>2013-14-1</p> <p>Disaster Information Management System, The United Nations Office for Disaster Risk Reduction (UNISDR, 2016)</p> <p><a href="http://www.desinventar.net/DesInventar/profi
letab.jsp?countrycode=npl&continue=y">http://www.desinventar.net/DesInventar/profi letab.jsp?countrycode=npl&continue=y</p>
Nmigrant	Number of migrants from the district gone to overseas for employment (2008-2014)	Number	<p>Department of Foreign Employment, Government of Nepal (GoN 2014)</p> <p><a href="https://asiafoundation.org/resources/pdfs/Mig
rationReportbyGovernmentofNepal.pdf">https://asiafoundation.org/resources/pdfs/Mig rationReportbyGovernmentofNepal.pdf</p>
Fuelwood	Total number of households using fuelwood for cooking	Number	<p>National Population and Housing Census (National Report), Central Bureau of Statistics (CBS), Government of Nepal (CBS, 2012)</p> <p><a href="http://cbs.gov.np/sectoral_statistics/populatio
n/national_report">http://cbs.gov.np/sectoral_statistics/populatio n/national_report</p>
Tloss	Net change loss in tree cover from 2001-2016	Hectare	Global Forest Watch (Hansen et al., 2013)

			http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.4.html
Tgain	Net gain in tree cover from 2001-2016	Hectare	Global Forest Watch (Hansen et al., 2013) http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.4.html
Elevation	Altitude	Meter	Shuttle Radar Topographic Mission (SRTM) Digital Elevation Data (DEMs) https://lta.cr.usgs.gov/SRTM1Arc
Slope	Slope	Degree	Calculated from elevation in ArcGIS

Table 2 (on next page)

Coefficients of net change in tree cover

Table 2. Coefficients of tree cover loss and gain

Model 1: Proportion of tree cover loss		Model 2: Proportion of tree cover gain	
Variables	Estimate (Std. error)	Variables	Estimate (Std. error)
	4.0660 (1.162)***		-0.4183(0.1700)
Ncfug	-0.0036(0.0008)***	Ncfug	-0.0007 (0.0004)
Rcfug	0.0139(0.0073)***	Rcfug	0.0155 (0.0029)***
P2001	0.000002(0.0000007)**	Ppop	-0.000002(0.000001)
HDI	-7.153(2.609)**	Fuelwood	0.000006(0.000004)
Nmigrant	0.00002(0.000009)*	Fire	0.02562(0.00852)**
	$R^2= 0.54, p = < 0.00000$		$R^2= 0.40, p = < 0.00000$

*p=0.05, **p=0.01, ***p=0.001

Figure 1

Study area showing the tree cover loss in different districts of Nepal.

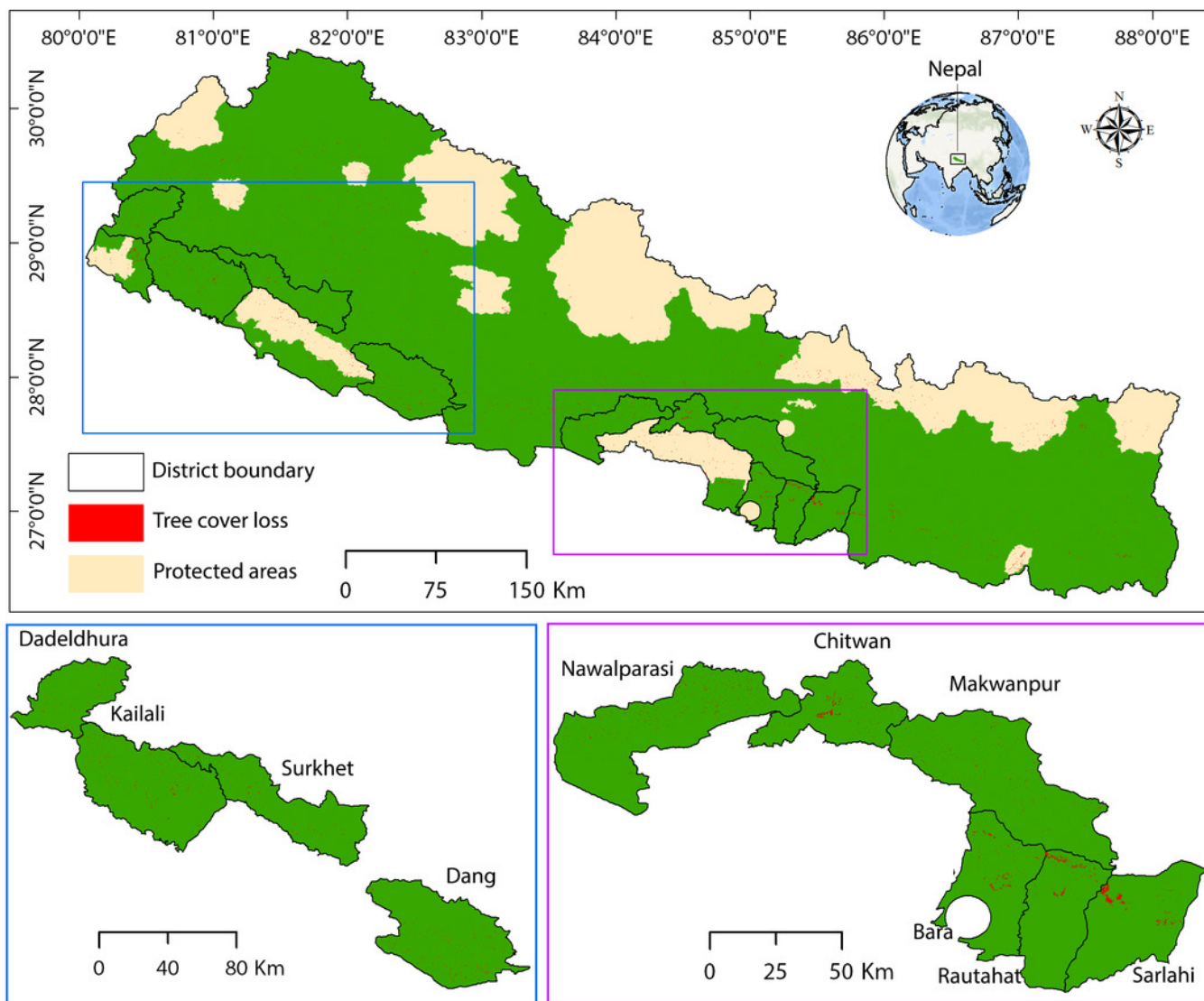


Figure 2

Extent of tree cover change in different districts of Nepal.

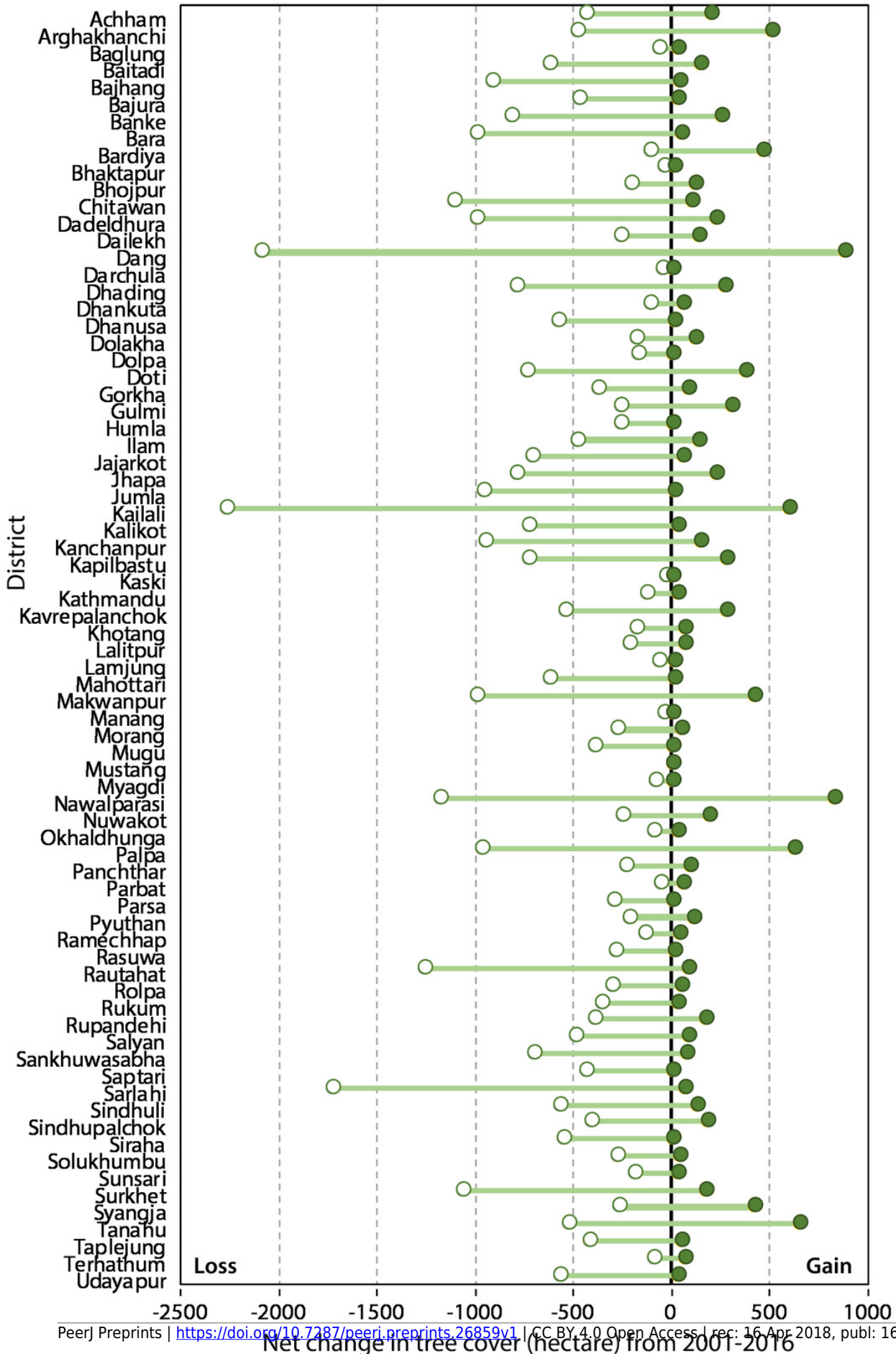


Figure 3

a) Tree cover loss and gain in distance from the road, b) Temporal pattern of tree cover loss in five physiographic regions of Nepal, c) Temporal pattern of tree cover loss with respect to forest fire incidence.

