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The Importance of Monitoring Rules in Local-Level Forest Management

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1. The Puzzle

Current studies of community level resource management focus on how individuals' incentives impede or help to overcome their collective action problems. While scholars have offered a long list of variables that may affect individuals' incentives, they have been far less successful in identifying the necessary or sufficient factor(s) for successful outcomes (however defined) (Agrawal 2002). Further, only a handful of studies have tested hypotheses with sample sizes of more than a dozen cases, and even those are generally drawn from the same geographic region. These studies obviously do not generalize across forests in different regions and of different types.

A3

We argue that despite the possible differences between individuals or the characteristics of the resource they use, the regular monitoring of rules is a necessary condition for successful resource management. This is not to say that the attributes of individuals or resources do not contribute to the creation and monitoring of rules—such research, in fact, is at the core of understanding the relationships between individuals and their environment. Our research, instead, challenges those who may think that it is only by such attributes that successful outcomes can occur; that certain sets of characteristics can bypass the regular monitoring of rules. Further, we attempt to generalize this argument by testing it with a significantly larger dataset than is usually found in this literature. Theoretical debates about what variables are significant or not to local level resource management will not be easily settled with such larger N empirical testing.

We test the importance of regular rule monitoring by pairing it with three other factors that often appear on analysts' lists of significant factors: the level of social capital in a group, whether or not a group is formally organized, and how dependent a group is on their resource. More specifically, we explore how the interaction of regular monitoring and sanctioning related to rules and the other variables might be related to forest condition. We find that the regular monitoring and sanctioning tends to dominate the other factors with regard to the probability that a forest is in good condition. That is, regardless of the levels of social capital, forest dependence, or formal organization, regular monitoring and sanctioning of whatever rules are actually in place is related to better forest conditions, and that irregular monitoring and sanctioning of rules is associated with poorer forest conditions. The data we employ comes from the work of the International Forestry Resources and Institutions Research Program.

2. Methods

Our original intent in analyzing over 112 forests from the IFRI data set was to perform regressions to provide structural interpretations of the relations between social capital and other variables and the condition of the forests, the dependent variable. A structural model is a causal model *as long as the analyst provides the correct specification.* Of course, this condition cannot be known, so the analyst must consider thought experiments to know how realistic the specification may be (see Learner 1978, 1983). In doing so, we realized that there are daunting impediments to creating a structural model for this data and our theory. These are listed below.

2a. Selection bias. A very common problem in the analysis of policy and policy outcomes is selection bias (Heckman 1974; Achen 1986). Let's give you an important example from our work. An important connection that we are interested in is whether the level of rules improves the condition of a forest. Since the data is non-experimental, so that we cannot manipulate rules to find out its effect on forest conditions, then we are not sure if the correlation between rules and forest conditions is due to the effect of the sanctioning or the fact that groups are more likely to have rules if the forest is in a bad condition. The problem that selection bias poses is in large part a problem due to our limited cross-sectional research design. But most non-experimental data are of this type, and Heckman (see Achen's treatment for better intuition) and others have offered statistical remedies. The results from these remedies are very sensitive to choice of specification (see Achen 1986).

2b. **Relational data base.** As described in Gibson, McKean, and Ostrom (2000), the IFRI data is in the format of a complex relational data base with many different connections among settlements, user groups, forest associations, forests, non-harvesting associations, etc. This complexity forces analysts to make important decisions before a rectangular or flat file can be provided for analysis. We describe some of our key decisions in Appendix A of this paper. Given that analysis is in essence contextual, there are issues about hierarchical data analysis that must be dealt with (Raudenbush and Bryk 2002). The problem is that the variables are at different levels of analysis. When this occurs, calculation of the variances for parameter estimates of interest become complicated, so that undertaking accurate hypothesis tests is not straightforward like it is with non-relational databases.

2c. Missing Cases. It is well understood that the loss of information due to missing cases can result in very imprecise regression results (Little and Rubin 1987). Imputing values instead of deleting cases that have one or more missing value will deliver more precise results in all cases (unless the imputation procedure is terrible). The reason for missing cases in the IFRI data set are many, and as a "living" data set many of the missing cases will ultimately be completed. However, for the regression we were interested in analyzing, there were 29 User Groups with multiple key variables missing (see Appendix A).

Typically, statistical fixes for problems and assumption violations in regression are developed in isolation from other problems. In our situation, we have three major issues confounding our data analysis. Furthermore, our number of cases relative to explanatory variables, 172 User-Group/Forest pairs, is actually quite small for dealing with these problems, especially the problem of selection bias. Thus, rather than try to estimate a structural regression model, we choose to approach the problem a bit differently.

We have three explanatory variables we focus on: a group's social capital, whether the group is a formal organization or not, and the regularity with which individuals in a user group monitor or sanction the behavior of other individuals for their conformance to local rules. We have two dependent variables, both measuring the condition of the forest based on a self-assessment of the user group. One of these variables is based on an assessment of the condition of the forest, the other on an assessment about how the condition of the forest has changed over time. We generate six three-way tables, and given that the monitoring variable is our focus variable, it is always in one of the tables. We report only the results for the tables that used dynamic forest condition, given that the results from both the static and dynamic measures of forest condition are largely the same (see Tables 1,2, and 3).

The general idea is to use expectations from theory to predict the pattern in these three-way tables. It is important to understand that we are looking for patterns in the tables—as exhibited in Figures 1-3—and not statistically driven causal relationships. In short, our theory can predict a pattern, and we can try to match the pattern to the theory.

3. Hypotheses

We posit one general hypothesis: that regular monitoring of rules is necessary for better forest conditions. We delineate the effect of this general hypothesis on the relationships between social capital, monitoring of rules, and forest condition below. (Our hypotheses appear as solid arrows in the figure.)

Social Capital (Figure 1.)

Hypothesis A. If social capital is low and monitoring of rules is sporadic, we expect forest condition to be low.

Hypothesis B. If social capital is low and monitoring of rules is regular, we expect forest condition to be high.

Hypothesis C. If social capital is high and monitoring of rules is sporadic, we expect forest condition to be low.

Hypothesis D. If social capital is high and monitoring of rules is regular, we expect forest condition to be high.

We theorize that consistent monitoring of rules is necessary to good outcomes in forest management. Whether or not a community has a high level of social capital, it will still need to monitor whether members of the group are actually conforming to their own agreements about how to manage a resource (e.g., Ostrom 1990; Gibson and Koontz 1998). Without monitoring, agreements may become meaningless within a short time.

We argue that the same pattern will hold in the relationships between monitoring and formal organization of user groups (Figure 2), and monitoring and a group's dependence on forest resources (Figure 3): where the monitoring of rules is regular, we expect better forests; where it is sporadic, worse forests, regardless of the level of formal organization or forest dependence.

4. Results

The explanatory and dependent variables produce six tables for analysis, three of which are included at the end of this paper. To provide an easy visual examination of the results, we have produced figures that give the results based on chi-square tests of significance for each sub-table.

Figure 1. Figure 1 shows the relationship of dynamic forest condition with regularity of monitoring and level of social capital. To keep cell values large, we have dichotomized each variable, and this is the case for the table on which each figure is based (see Tables 1-3). For this dependent variable, what we find is that social capital does not appear to matter. Regular monitoring of rules correlates with good forest conditions, and sporadic monitoring of rules correlates with poor forest conditions. These results are significant at the .01 level. Thus, there is significant empirical support for all four hypotheses we proposed for the relationship among the regularity of monitoring, social capital, and dynamic forest conditions. Further, no outcome contrary to our hypothesis is statistically significant.

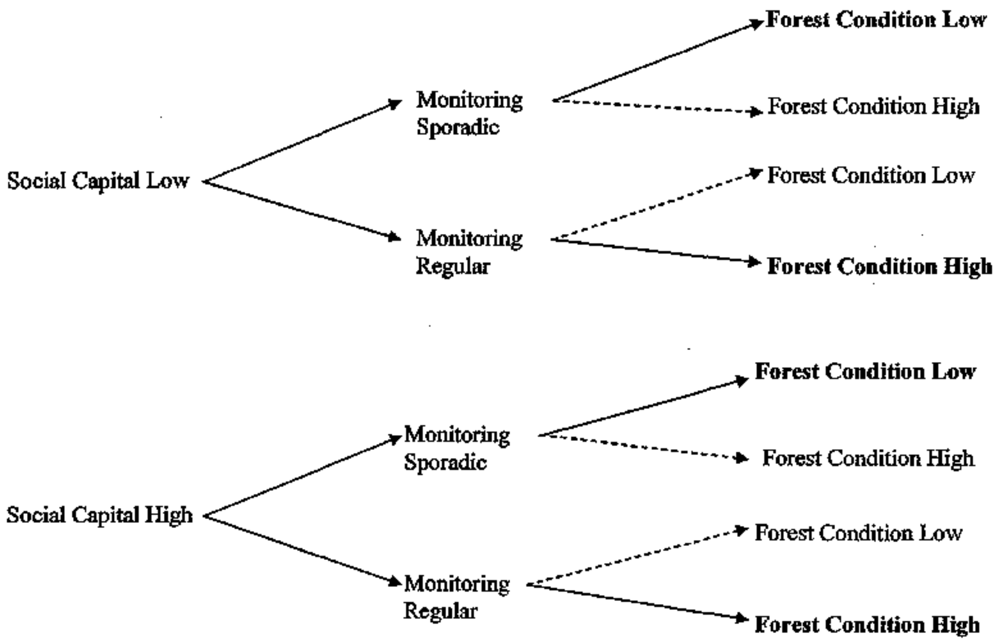
Figure 2. Now we look at how formal group organization might influence forest conditions. Our hypotheses about the importance of monitoring find significant empirical support only in the case of no formal organization and sporadic monitoring of rules. However, no significant outcomes are contrary to our hypotheses.

Figure 3. This figure presents the results for the relationship between forest dependence and the regularity of rule monitoring. Here we see outcomes like in Figure 1: all four hypotheses that correspond to the importance of monitoring of rules are statistically significant. No outcomes contrary to our hypotheses are statistically significant.

5. Discussion

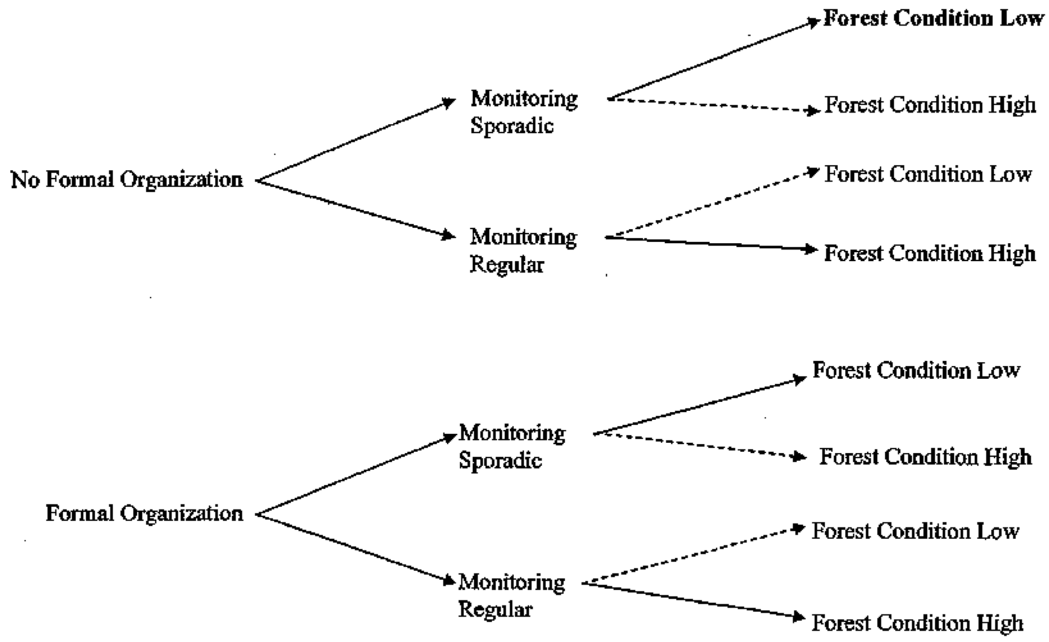
While our analysis is consistent with considerable research focusing on the governance and management of common-pool resources[1], it also challenges more recent work regarding the importance of social capital. Unless members of a User Group or a Government Forestry Department appoints an official guard, or the members of the User Group themselves monitor each other when using a forest, it is unlikely that any formal rules that are imposed by either a government agency or the users will be very effective. This initial working paper demonstrates that relationship clearly. Further, the analysis shows that this relationship is a strong predictor of better forest conditions: the levels of social capital, formal organization, and forest dependence on the other hand, did not affect the pattern of outcomes. We will proceed to examine how social capital, formal organization, and dependence on a forest affect other intermediate variables and how several other variables already coded in the IFRI database are also related to forest conditions including the appointment of forest guards, the relationship between the number of guards (and their payments) in relationship to the size of the forest.

Figure 1. Relationships between Social Capital, Dynamic Forest Condition, and Regularity of Monitoring/Sanctioning of Rules



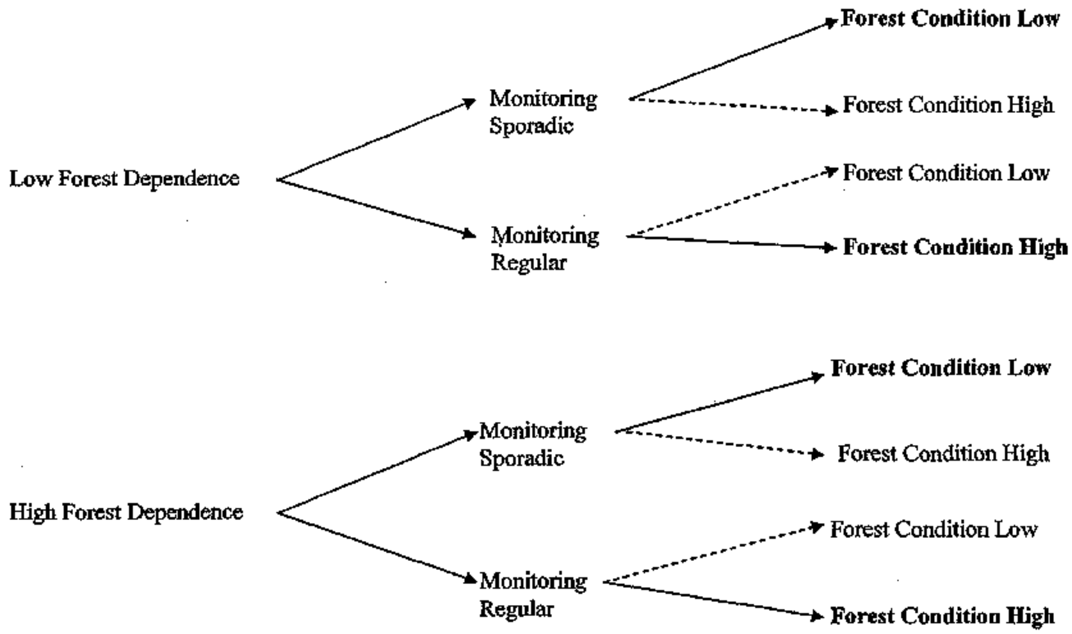
Solid arrows indicate paths of hypotheses;
bold type implies a significant χ^2 test at $p < .10$.

Figure 2. Relationships between Formal Organization, Dynamic Forest Condition, and Regularity of Monitoring/Sanctioning of Rules



Solid arrows indicate paths of hypotheses;
bold type implies a significant χ^2 test at $p < .10$.

Figure 3. Relationships between Forest Dependence, Dynamic Forest Condition and Regularity of Monitoring/Sanctioning of Rules



Solid arrows indicate paths of hypotheses;
bold type implies a significant χ^2 test at $p < .10$.

Table 1: Social capital factor score 1 * (dynamic forest condition x in-forest sanctions), all years, original sanctions

dichdyn: Dichotomized dynamic forest condition factor scale (0-2 = low; 3-6 = high) * dichsini: Dichotomized ub4_5ai (inverted usanctin) [1-2 = low; 3-4 = high] * dichsc1i: Dichotomized social capital factor scale 1i (3 = low; > 3 = high) Crosstabulation

Count

dichsdi: Dichotomized social capital factor scale 1i(3 = low; > 3 = high)			dichsini: Dichotomized ub4_5ai (inverted usanctin) [1 -2 = low; 3-4 = high] low	high	Total
low	dichdyn: Dichotomized dynamic forest condition factor scale (0-2 = low; 3-6 = high)	low	41	10	51
		high	19	16	35
	Total		60	26	86
high	dichdyn: Dichotomized dynamic forest condition factor scale (0-2 = low; 3-6 = high)	low	22	10	32
		high	6	14	20
	Total		28	24	52

original sanctions: never, occasionally = Low; seasonally, year-round = High

dichsc1i (low): Pr[dichdyn = low|dichsini = low] = Pr[dichdyn = low ∩ dichsini = low]/Pr[dichsini = low] = 41/60 = .683

dichsc1i (high): Pr[dichdyn = low|dichsini = low] = 22/28 = .786

Chi-Square Tests

dichsd1i: Dichotomized social capital factor scale		Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
low	Pearson Chi-Square	6.707[b]	1	.010		
	Continuity Correction[a]	5.526	1	.019		
	Likelihood Ratio	6.661	1	.010		
	Fisher's Exact Test				.016	.010
	Linear-by-Linear Association	6.629	1	.010		
	N of Valid Cases	86				
high	Pearson Chi-Square	7.436[c]	1	.006		
	Continuity Correction[a]	5.959	1	.015		
	Likelihood Ratio	7.595	1	.006		
	Fisher's Exact Test				.010	.007
	Linear-by-Linear Association	7.293	1	.007		
	N of Valid Cases	52				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 10.58.

c. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.23.

Table 2: Formal organization * (dynamic forest condition x in-forest sanctions), all years, original sanctions

dichdyn: Dichotomized dynamic forest condition factor scale (0-2 = low; 3-6 = high) * dichsini: Dichotomized ub4_5ai (inverted usanctin) [1-2 = low; 3-4 = high] * ub1 rcdd6: Is user group formally organized? Crosstabulation

Count

ub1rcdd6: Is user group formally organized?			dichsini: Dichotomized ub4_5ai (inverted usanctin) [1-2 = low; 3-4 = high] low	high	Total
no, not formally organized	dichdyn: Dichotomized dynamic forest condition factor scale (0-2 = low; 3-6 = high)	low	56	7	63
		high	11	5	16
	Total		67	12	79
yes, formally organized	dichdyn: Dichotomized dynamic forest condition factor scale (0-2 = low; 3-6 = high)	low	11	16	27
		high	14	30	44
	Total		25	46	71

original sanctions: never, occasionally = Low; seasonally, year-round = High

ublrcdd6 (No): Pr[dichdyn = low | dichsini = low] = 56/67 = .836

ublrcdd6 (Yes): Pr[dichdyn = low | dichsini = low] = 11/25 = .44

Chi-Square Tests

ub1rcdd6: Is user group formally organized?		Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
no, not formally organized	Pearson Chi-Square	4.017[b]	1	.045		
	Continuity Correction[a]	2.606	1	.106		
	Likelihood Ratio	3.479	1	.062		
	Fisher's Exact Test				.060	.060
	Linear-by-Linear Association	3.966	1	.046		
	N of Valid Cases	79				
yes, formally organized	Pearson Chi-Square	.584[c]	1	.445		
	Continuity Correction[a]	.258	1	.611		
	Likelihood Ratio	.580	1	.446		
	Fisher's Exact Test				.456	.304
	Linear-by-Linear Association	.576	1	.448		
	N of Valid Cases	71				

a. Computed only for **a** 2x2 table

b. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 2.43.

c. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.51.

Table 3: Forest dependence * (dynamic forest condition x in-forest sanctions), all years, original sanctions

dichdyn: Dichotomized dynamic forest condition factor scale (0-2 = low; 3-6 = high) * dichsini: Dichotomized ub4_5ai (inverted usanctin) [1-2 = low; 3-4 = high] * fde prcd: What is the level of dependence on the forest for commercial income (fdepscl)? Crosstabulation

Count

fdeprcd: What is the level of dependence on the forest for commercial income (fdepscl)?			dichsini: Dichotomized ub4_5ai (inverted usanctin) [1 -2 = low; 3-4 = high] low	high	Total
low (none)	dichdyn: Dichotomized dynamic forest condition factor scale (0-2 = low; 3-6 = high)	low	17	9	26
		high	7	17	24
	Total		24	26	50
high (some)	dichdyn: Dichotomized dynamic forest condition factor scale (0-2 = low; 3-6 = high)	low	44	12	56
		high	17	17	34
	Total		61	29	90

original sanctions: never, occasionally = Low; seasonally, year-round = High

fdeprcd (low): Pr[dichdyn = low | dichsini = low] = 17/24 = .708

fdeprcd (high): Pr[dichdyn = low | dichsini = low] = 44/61 = .721

Chi-Square Tests

fdeprcd: What is the level of dependence on the		Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
low (none)	Pearson Chi-Square	6.559[b]	1	.010		
	Continuity Correction[a]	5.188	1	.023		
	Likelihood Ratio	6.718	1	.010		
	Fisher's Exact Test				.013	.011
	Linear-by-Linear Association	6.428	1	.011		
	N of Valid Cases	50				
high (some)	Pearson Chi-Square	7.908[c]	1	.005		
	Continuity Correction[a]	6.653	1	.010		
	Likelihood Ratio	7.809	1	.005		
	Fisher's Exact Test				.010	.005
	Linear-by-Linear Association	7.820	1	.005		
	N of Valid Cases	90				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 11.52.

c. 0 cells (.0%) have expected count less than 5. The minimum expected count is 10.96.

Appendix A. Description of User Groups Included in this Study

Many scholars and officials presume that unless a government has established a formal forest users' group, that few forest users will take any action—let alone organize themselves effectively—to protect the forest resources that they use. When scholars associated with the IFRI research program go to the field, however, we find a large variance in the type of uses made of forests (the type of products harvested, the recreational uses, and the ecosystem service uses) as well as the kinds of activities and organizational arrangements of users. User Groups vary significantly in regard to whether the users themselves are willing to participate in monitoring or sanctioning behavior.

Before we could begin to address this question, however, we need to sort out a clear reference group of User Groups to be used in our analysis. In our IFRI research, we frequently find that a forest is used by one or more "User Groups" who may (or, sometimes, may not) have formal legal rights. The User Group may be organized in the sense that they meet regularly, elect officials, and have agreed upon rules and procedures. Or, the group may simply use the forest based on similar customary rights without organizing themselves. Further we often find more than one User Group using the same forest.

For the analysis in this paper, we have limited ourselves to data collected at the time of the first data collection visit by colleagues associated with the IFRI research network. The paper is based on data collected from the first research visits to forests located in 12 countries.[2] For each of the forests included, we have identified one or more User Group per forest for the current analysis since we are linking aspects of group structure to forest conditions.[3]

The 172 User Groups included in this study varies substantially in their level of activities. Some sets of users do not meet with one another at all and do not share any level of activities. Of the sets of users included in our study, so far we have located 29 sets of users who do not undertake any *collective* activity in regard to the forest they use. This is only 16.9 percent of the full set of users we have identified.

On the other hand, we have identified 75 User Groups that have organized themselves sufficiently to hold at least some meetings, elect officials, and undertake at least some joint activities. There is also a large set in the middle. There are 62 User Groups who do not elect officials and do not have a joint budget, but do undertake at least one kind of joint activity. And, there a 5 formally constitute User Groups who do not undertake any collective activities at all.

The User Groups in this study also vary rather dramatically in age. We have identified several groups who were organized long before the eighteenth century. Table Appendix A-l provides a list of groups that were formed before, their name, date of their formation, and where they are located. As the reader will notice, most of these are from Mexico, Nepal and Tanzania.

In total, we identified 26 sets of users that had been using the same forest for more than a hundred years. Of this group, 6 were formally organized and 20 were simply sets of users continuing to use the same forest resources without organization for more than a century.

Appendix Table A-l: User Groups Older Than 100 Years

User Group Name (uname)	Forest Name (fname)	Country	Formally Organized?	Year Started
Female and Children	Nkweshoo	Tanzania	Yes	1300
Male	Nkweshoo	Tanzania	Yes	1300
Comunidad de Capulalpams	Bosque Para El Uso Domestico	Mexico	Yes	1400
Gurje-Ahal Bhanjyang Forest User Group	Gurje-Ahal Bjanjyang	Nepal	No	1595
Gambhire-Simpani Forest User Group	Gambhire-Simpani	Nepal	No	1597
Comuneros y sus Familias	Donaciano Ojeda	Mexico	Yes	1617
Habitantes de Donaciano Ojeda	Donaciano Ojeda	Mexico	Yes	1617
Bukasa Women User Group	Mugomba	Uganda	No	1700
Vanga Firewood Collectors	Vanga Forest Outpost	Kenya	No	1700
Tesoro User Group	Tesoro Community	Guatemala	Yes	1790
Subsistence Fuelwood Collectors	Butto-buvuma	Uganda	No	1800
Kiziiko Firewood Collectors	Najjakulya Private	Uganda	No	1800
Las Cebollas Community Members	Communal Forest	Guatemala	No	1800
Ghympe-Bohare Khola Forest User Group	Ghampe-Bohare Khola	Nepal	No	1846
Chharchhare Pakha Forest User Group	Chharchhare Pakha	Nepal	No	1846
Nehit Forest User Group	Nehit	Nepal	No	1847
Propietarios de Chapis	Bosque de Chapis	Bolivia	No	1860
Comunarios de La Merced	La Merced	Bolivia	No	1870
Women (Subsistence firewood user group)	Mpanga Nature Reserve	Uganda	No	1890
Herbajeros de Chapis	Bosque de Chapis	Bolivia	No	1890
Asentados de Chapis	Bosque de Chapis	Bolivia	No	1895
Ejidos avenos	Zona Amortiguamiento	Mexico	No	1900
Water Collectors	Mt. Elgon (Chorlem Block)	Kenya	No	1900
Herbalists	Loitokitok (Kikelelwa Forest)	Kenya	No	1900
Firewood collectors	Loitokitok (Kikelelwa Forest)	Kenya	No	1900
Grass cutters / livestock herders	Loitokitok (Kikelelwa Forest)	Kenya	No	1900

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Notes

[1] See, for example, chapters by Agrawal, McCay, Rose, Tietenberg, and the concluding chapter in Ostrom et al. 2002.

[2] Bolivia, Brazil, Ecuador, Guatemala, Honduras, Kenya, India, Mexico, Nepal, Tanzania, Uganda, United States.

[3] We started with a data set of 238 User Group-Forest pairs. We removed 37 second visits from the dataset to preclude double coding of the same forest. The next problem was how to treat analytical problems arising from the multiplicity of relationships between User Groups and forests. User Groups sometimes utilize more than one forest. Further, a forest can be utilized by more than one User Group. We decided for this analysis to cope with the analytical problem of one User Group using more than one Forest in two stages. First, we compared the number of missing cases in each pair and eliminated those User Group-Forest pairs that had ten more missing data points than the other relevant pair. Second we used a random flip of the coin to eliminate the remaining pairings. A total of 29 cases were removed in this way. We ended up with 172 User Group-Forest Pairs that represent 112 unique forests. We retained the cases in the data set where one forest was used by multiple User Groups. Thirty-three of the forests have multiple User Groups accessing their resource. In our analysis, we found only two of the 33 forests where the dichotomous coding of regularity of monitoring differed among User Groups using that forest.