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POVERTY AND CORRUPTION COMPROMISE TROPICAL FOREST RESERVES

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Abstract. We used the global fire detection record provided by the satellite-based Moderate Resolution Imaging Spectroradiometer (MODIS) to determine the number of fires detected inside 823 tropical and subtropical moist forest reserves and for contiguous buffer areas 5, 10, and 15 km wide. The ratio of fire detection densities (detections per square kilometer) inside reserves to their contiguous buffer areas provided an index of reserve effectiveness. Fire detection density was significantly lower inside reserves than in paired, contiguous buffer areas but varied by five orders of magnitude among reserves. The buffer : reserve detection ratio varied by up to four orders of magnitude among reserves within a single country, and median values varied by three orders of magnitude among countries. Reserves tended to be least effective at reducing fire frequency in many poorer countries and in countries beset by corruption. Countries with the most successful reserves include Costa Rica, Jamaica, Malaysia, and Taiwan and the Indonesian island of Java. Countries with the most problematic reserves include Cambodia, Guatemala, Paraguay, and Sierra Leone and the Indonesian portion of Borneo. We provide fire detection density for 3964 tropical and subtropical reserves and their buffer areas in the hope that these data will expedite further analyses that might lead to improved management of tropical reserves.

Key words: biodiversity; corruption; fire; Indonesia; national parks; poverty; protected areas; remote sensing; tropical forest; wealth.

Introduction

Tropical deforestation is among the greatest threats to the preservation of global biodiversity (Millennium Ecosystem Assessment 2005). Tropical and subtropical nations have created an immense system of nature reserves to ameliorate this threat. The World Database on Protected Areas (WDPA), which is incomplete, delineates the boundaries of 1938 reserves that encompass 1.63×10^6 km^2 of forest between the Tropics of Cancer and Capricorn alone (WDPA Consortium 2004). Just these nationally recognized reserves represent 7.3% of the preagricultural extent of tropical forest and 15% of extant tropical forest (Ramankutty and Foley 1999, Achard et al. 2002, Hansen and DeFries 2004). Indigenous areas, reserves recognized by subnational levels of government, and nationally recognized reserves not yet entered into the WDPA will all increase the total area protected (Nepstad et al. 2006). Collectively these reserves should make a substantial contribution to the conservation of biodiversity in the tropics.

There is considerable debate, however, about the effectiveness of these protected areas, with concern that many tropical reserves are ineffective "paper parks" unable to protect the biodiversity within their borders against growing anthropogenic pressure (Terborgh et al. 2002, Smith et al. 2003*a*, Curran et al. 2004). Recent studies indicate that many tropical reserves do reduce the impact of a wide range of human activities including grazing, hunting, fire, logging, and forest clearing (Bruner et al. 2001, Vanclay et al. 2001, DeFries et al. 2005, Nepstad et al. 2006); however, we still lack a global assessment of the effectiveness of all tropical forest reserves. Here, we use the global fire detection record provided by the satellite-based Moderate Resolution Imaging Spectroradiometer (MODIS) to determine whether protected status influences fire occurrences for every tropical reserve with boundaries delineated in the WDPA.

We limit our analyses to moist forests because natural fire return times can extend to centuries in tropical moist forests, and human activities increase fire frequency above these low background levels (Cochrane 2003). Human activities that increase fire frequency include timber extraction and land use conversion. Timber extraction increases fuel loads and dries forest microclimates (Cochrane 2003). Forest clearing creates forest–field edges and remnant forest fragments that are highly susceptible to fire (Cochrane 2003, Laurance 2004). Fire is also used purposefully to clear forest, to control natural regrowth, and to manage agricultural lands (Kull 2004, Rudel 2005). Thus, fire provides an indicator of timber extraction and land use conversion that moist

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forest reserves should prevent. We calculate fire detection density (detections per square kilometer per year) inside reserves and inside contiguous buffer areas extending in all directions from the borders of each reserve and use the ratio of these two values to quantify the relative impact of reserve status on the local occurrence of fire. We then use the buffer : reserve fire detection ratio to examine national-level variation in reserve effectiveness for 37 tropical countries that differ widely in extant forest capital, economic development, and human population density.

Methods

Fire detection density

The MODIS Rapid Fire Response System (information *available online*)[5] provided 1-km^2 resolution fire detections for 2002–2004 for the Terra satellite and from October 2002 through 2004 for the Aqua satellite. MODIS fire products are created using a global active fire algorithm developed, validated, and refined by Giglio et al. (2003) and Morisette et al. (2002, 2005). The MODIS active fire algorithm uses a contextual approach that exploits the strong emission of mid-infrared radiation from fires. The algorithm assigns each 1-km pixel to one of the following classes: fire, non-fire, missing data, cloud, water, or unknown. We assume the presence of cloud is similar for reserves and their contiguous buffer areas (see *Discussion* for a possible exception). A detected fire represents the center of a pixel flagged as containing one or more actively burning fires. It is not possible to determine the exact size of a fire represented by a pixel, but MODIS routinely detects both flaming and smoldering fires much smaller than 1 km^2 (Giglio et al. 2003). MODIS is unlikely to detect low intensity ground fires under a closed forest canopy. The MODIS active fire detection algorithm is applied to day and nighttime data from the Aqua and Terra satellites, which provides approximately four active fire products per day for most land surfaces.

Two additional sources provided the information required to calculate biome-dependent fire detection densities for reserves. The Global Land Cover Facility (information *available online*)[6] provided boundaries for reserves listed in the WDPA (WDPA Consortium 2004). These reserves are nationally recognized, fulfill the World Conservation Union (IUCN) definition of a protected area—"An area of land and/or sea especially dedicated to the protection and maintenance of biological diversity, and of natural and associated cultural resources, and managed through legal or other effective means" —, and include IUCN management categories I through VI (IUCN 1994). The World Wildlife Fund (information *available online*)[7] provided global boundaries for 14 biomes (Olson et al. 2001). The biome of concern here is described as "tropical and subtropical moist broadleaf forest." Henceforth, we use tropical moist forest to refer to the tropical and subtropical moist broadleaf forest biome.

We used ArcGIS software to determine the potential representation of each biome inside each reserve; to produce vectorial layers representing buffer areas; and to count fires inside reserves and buffer areas. The 1-km^2 spatial resolution of MODIS fire detections precluded the use of buffers narrower than 5 km and reserves smaller than 50 km^2. The WDPA and Terrestrial Ecoregions databases provided vectorial (polygon) information on the location and extent of each reserve and biome, respectively. We used a spatial joining with fire detections from 2002, 2003, and 2004 to calculate fire detection density (detections per square kilometer per year) for each biome inside each reserve. Most reserves included a single biome or small areas of additional biomes that taxed the 1-km^2 spatial resolution of MODIS fire detections. We therefore collapsed the fire detection by biome data to obtain a single estimate of fire detection density inside each reserve and limited analyses to reserves where tropical moist forest was the potential vegetation cover over more than 90% of reserve area. A second spatial joining provided fire detection density for each buffer area. Buffer areas extended 5, 10, or 15 km from each reserve boundary and excluded contiguous reserves. Twenty-four reserves were completely enclosed within other reserves, lacked an unprotected buffer area, and were excluded from all analyses. Computational limitations precluded determining surface cover for buffer areas so we also excluded reserves whose contiguous buffer areas contained lake or ocean surfaces. We repeated all analyses for buffer areas of three different widths to bracket the relative areas of reserves and buffer areas. Buffers 5, 10, and 15 km wide are approximately 5-, 12-, and 20-fold larger than the smallest 50-km^2 reserve depending on its shape and approximately equal in area to 600-, 2000-, and 10 000-km^2 reserves, respectively.

Sample sizes

The WDPA lists 2377 reserves that include any of the four tropical or subtropical forest biomes (mangrove, coniferous, dry broadleaf, or moist broadleaf; WDPA Consortium 2004). The moist broadleaf forest biome is present in 1955 reserves and dominates (>90% coverage) 1530 reserves, including 937 reserves larger than 50 km^2 of which 827 lack open water inside their contiguous buffer areas. We excluded three additional reserves because an active volcano repeatedly triggered the MODIS fire detection algorithm and one final reserve because it was mistakenly located inside a Philippine city (Supplement). The 823 reserves that remain are located between 34° S and 30° N. Tree diversity declines sharply near 30° N and S latitude (Gentry 1988) making this an appropriate latitudinal limit for our analyses. The

[5] ⟨http://maps.geog.umd.edu⟩
[6] ⟨http://www.landcover.org⟩
[7] ⟨http://www.worldwildlife.org/science⟩

countries represented (and numbers of reserves) follow: Argentina (4), Belize (10), Bolivia (8), Brazil (41), Colombia (19), Costa Rica (24), Cuba (1), Dominica (1), Ecuador (9), French Guiana (2), Guatemala (17), Guyana (1), Honduras (2), Jamaica (4), Mexico (14), Nicaragua (11), Panama (11), Paraguay (7), Peru (10), Puerto Rico (1), Suriname (7), and Venezuela (20) in the Americas; Burundi (2), Cameroon (9), Central African Republic (2), Congo (5), Democratic Republic of the Congo (5), Equatorial Guinea (8), Gabon (2), Ghana (4), Guinea (2), Ivory Coast (4), Kenya (3), Liberia (1), Madagascar (17), Mozambique (1), Nigeria (2), Rwanda (2), Sierra Leone (4), South Africa (4), Swaziland (1), Tanzania (1), and Uganda (2) in Africa; and Bangladesh (5), Cambodia (8), China (162), Hong Kong (2), India (92), Indonesia (81), Laos (16), Malaysia (13), Myanmar (1), Philippines (44), Sri Lanka (2), Taiwan (7), Thailand (55), and Viet Nam (30) in Asia.

Analyses

We performed a non-parametric sign test to evaluate the null hypothesis that fire detection density was equal for reserves and their paired buffer areas. A non-parametric analysis was required because many reserves and several buffer areas lacked a single fire detection from 2002 to 2004. We also defined a buffer : reserve fire detection ratio as the ratio of fire detection density for each buffer area to fire detection density for the enclosed reserve. A small constant equivalent to 0.00001 fire detections$\cdot$km$^{-2}\cdot$yr^{-1} was added to every fire detection density so that this ratio was always finite.

We performed multiple regression analyses to evaluate relationships between the median buffer : reserve fire detection ratio and eight independent variables for the 37 countries with three or more qualifying reserves. The eight independent variables characterized extant forest capital and its recent trend (forested area per capita in 2000 and the 1990s deforestation rate), economic development (per capita gross domestic product and a human development index), population and its recent trend (population density in 2003 and population growth rate from 1975 to 2003), a corruption perception index, and the background fire detection density calculated for the entire country. Forward and backward selection procedures used significance levels of 0.15 for independent variables to enter and leave the regression model, respectively. The median buffer : reserve ratio was log-transformed, and the independent variables were untransformed to obtain normally distributed residuals. Regression analyses presume linear relationships. To detect other possible relationships, we inspected scatter plots for the buffer : reserve ratio and each of the eight independent variables.

Several sources provided independent variables. Transparency International provided the corruption perception index (CPI; Poroznuk 2005). Transparency International and the CPI are well respected by social scientists (Bukovansky 2006). The CPI is a "poll of polls," which ranks countries according to levels of corruption as perceived by international business persons, public officials, and general public opinion in polls conducted by various research institutes (Poroznuk 2005). The United Nations Food and Agriculture Organization provided 1990s deforestation rates (FAO 2001). The United Nations Development Programme provided the human development index (HDI), percentage of land area forested, per capita gross domestic product, and population density and population growth rate (UNDP 2003, 2005). The HDI incorporates longevity, adult literacy, school enrollment, and living standards. We used the land area of each country, the percentage forested, and population density to calculate per capita forest area (hectares per capita). The United Nations does not provide information for Taiwan. The CIA–World Fact Book (*available online*)[8] provided per capita gross domestic product, population density, and population growth rate for Taiwan. The HDI, deforestation rates, and percentage of land area forested were unavailable for Taiwan. We therefore repeated the analyses with and without Taiwan for each of three buffer widths generating six multiple regression analyses.

Results

Fire was detected in 575 of 823 tropical moist forest reserves between 2002 and 2004. Fire detection density varied over five orders of magnitude among these 575 reserves (Fig. 1) and was significantly lower inside reserves than in their paired buffer areas for all reserves ($n = 823$ reserves, sign test, $P < 1 \times 10^{-6}$ for 5-, 10-, and 15-km buffers) and for just those reserves where fire was detected ($n = 575$, sign test, $P < 1 \times 10^{-5}$ for 5-, 10-, and 15-km buffers).

The median buffer : reserve fire detection ratio varied by three orders of magnitude among the 37 countries with three or more qualifying reserves (Fig. 2). Just three of the eight independent variables entered significantly into one or more of the six (with and without Taiwan for three buffer widths) multiple regression models. The corruption perception index (CPI) entered all six models (Fig. 3, $2.52 < t < 4.59$, $0.00006 < P < 0.017$), per capita gross domestic product entered two models ($t = 2.31$, $P = 0.028$ and $t = 2.11$, $P = 0.043$ for 10- and 15-km buffers without Taiwan, respectively), and per capita forest area entered one model ($t = -2.20$, $P = 0.036$ for a 10-km buffer without Taiwan). Equatorial Guinea was an outlier from the relationship between the CPI and the median buffer : reserve ratio (Fig. 3, studentized residual $= 3.07$), and the percentage of variation explained by this one independent variable increased from 37% to 48% when Equatorial Guinea was excluded. The relationship with per capita gross domestic product was closer to triangular than to linear (data not shown). There was a

[8] ⟨www.cia.gov/cia/publications/factbook/index.html⟩

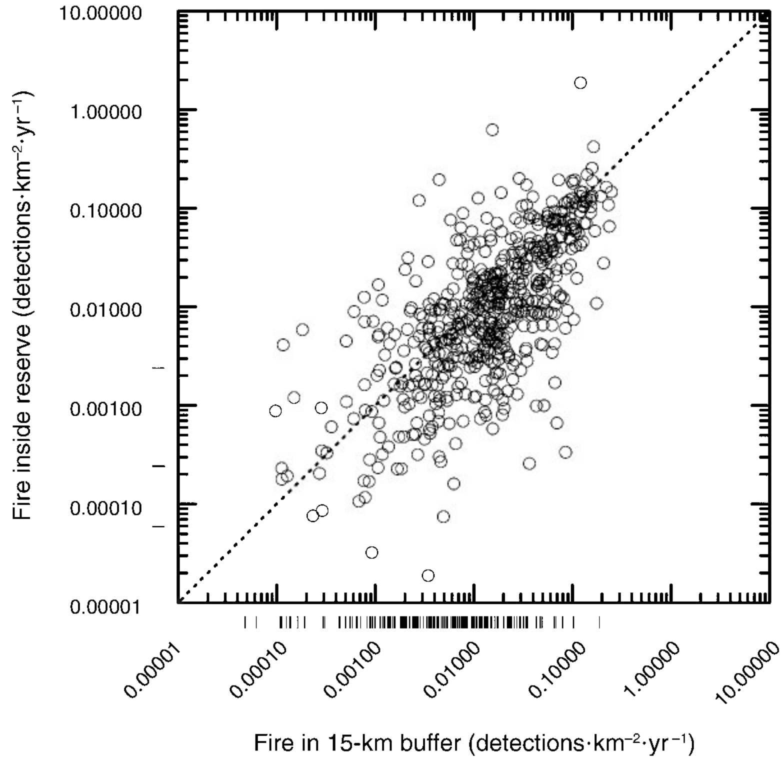

FIG. 1. Fire detection density inside and just outside 823 tropical and subtropical moist forest reserves (note log scales). The short vertical lines below the figure represent 224 cases where zero fires were recorded inside the reserve between 2002 and 2004. The short horizontal lines to the left of the figure represent six cases where zero fires were recorded inside the buffer areas. An additional 24 cases where zero fires were recorded inside both the reserve and its buffer area are omitted. The dotted line represents equal fire detection density inside and just outside reserves. Buffer areas extend 15 km from reserve borders in all directions. Each reserve is larger than 50 km^2, has moist broadleaf forest as the potential vegetation over more than 90% of its area, and lacks open water inside its buffer area.

similar triangular relationship with the human development index (HDI) such that the median buffer : reserve ratio varied widely among high income and high HDI countries and was always limited to low values for low income and low HDI countries, with the exception of Ghana (Fig. 4). There was no evidence for correlations between the median buffer : reserve ratio and human population traits nor the background countrywide fire detection density.

Relationships among the CPI, the HDI, and per capita gross domestic product limit the conclusions that can be drawn from the multiple regression analyses. The CPI and per capita gross domestic product are closely related when developed and developing countries are pooled (Smith et al. 2003*b*) and reasonably well related for the 37 developing countries considered here ($r^2 = 0.39$, $P < 0.001$). The HDI incorporates longevity, adult literacy, school enrollment, and an index of purchasing power parity, which is derived from local prices and per capita gross domestic product. Not surprisingly, the HDI is reasonably well related to per capita gross domestic product for the 36 countries considered here (the HDI is not available for Taiwan, $r^2 = 0.43$, $P < 0.001$). The relationships among these three variables preclude attributing variation in the buffer : reserve ratio to one of the three. Rather, we conclude that the buffer : reserve ratio tends to increase and tropical moist forest reserves tend to become more effective as human well-being improves and corruption declines (Figs. 3 and 4).

DISCUSSION

Our study has at least two limitations. First, we purposefully omitted site-level characteristics for each reserve to maintain a global, between-country perspective. The quality of site-level data varies widely among countries (consider Taiwan and the Democratic Republic of the Congo). We felt that this level of variation in data quality would compromise global analyses for most site-level characteristics. The second related limitation concerns possible within-site, environmental variation between reserves and buffers. Most environmental gradients are gradual relative to the distances across reserves and their buffers. Gradual environmental gradients will pass through buffer, reserve, and then buffer again (because each buffer area completely encircles the enclosed reserve) and are therefore unlikely to cause systematic differences between reserves and

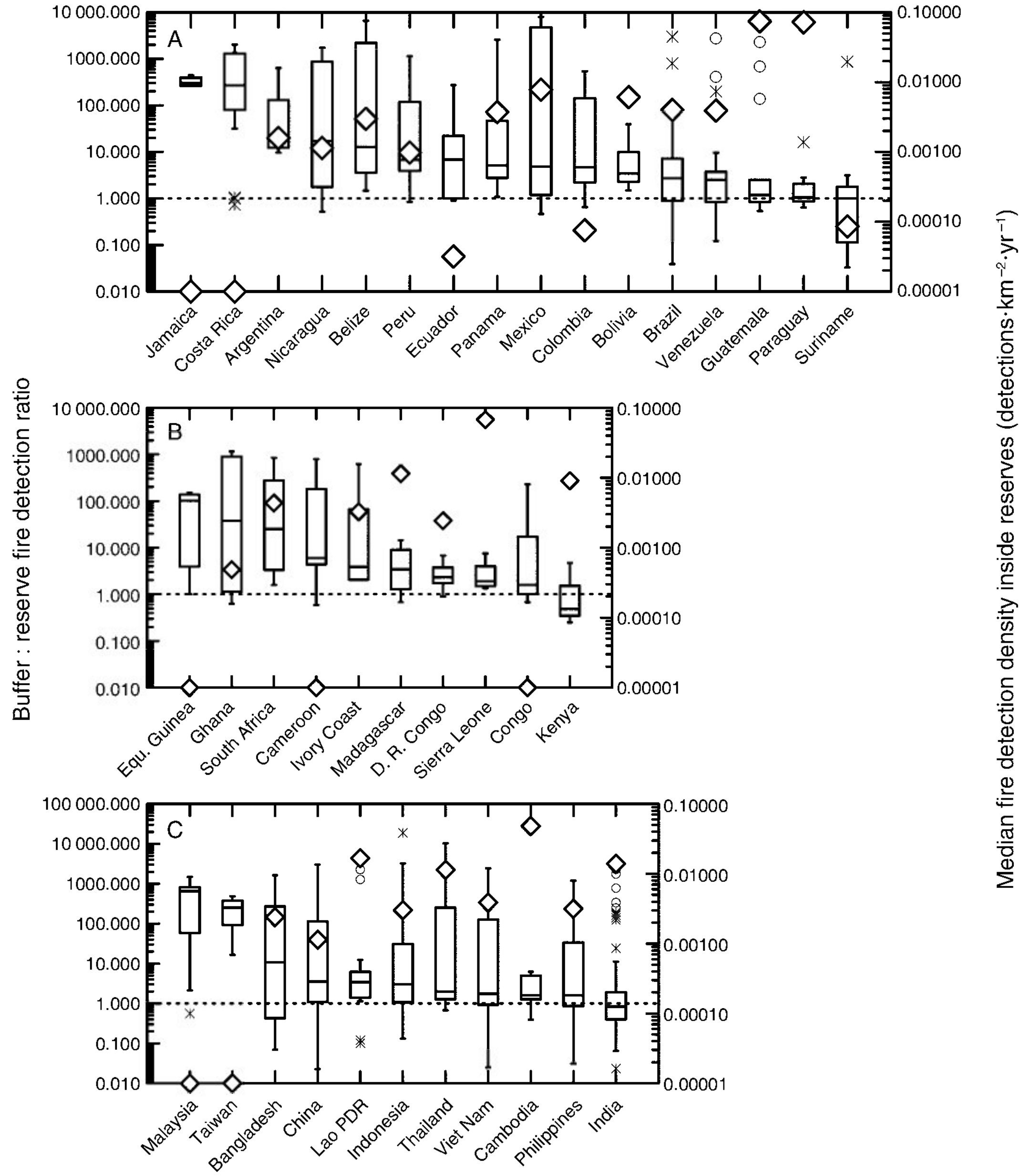

FIG. 2. The buffer : reserve fire detection ratio (box plots, left vertical scale) and median fire detection density inside reserves (open diamonds, right vertical scale) for tropical moist forest reserves from (A) the Americas, (B) Africa, and (C) Asia (note log scales). Countries are ordered by the median buffer : reserve ratio along the horizontal axis. The dotted, horizontal lines represent equal fire detection densities for reserves and their buffer areas. The minimum median fire detection densities inside reserves are actually zero and not 0.00001 fire detections·km^{-2}·yr^{-1} because this small constant was added to each fire detection density to ensure that the buffer : reserve ratio was always finite. Buffer areas extend 15 km from reserve borders in all directions. Each country has three or more reserves with boundaries delineated in the World Database on Protected Areas that are larger than 50 km^2 with moist broadleaf forest as the potential vegetation over more than 90% of the area and without open water inside its buffer area. For each box plot, the central horizontal line represents the median; the top and bottom horizontal lines are the first and third quartiles or hinges, respectively; the whiskers show the range of values within 1.5 inter-quartile ranges of the hinges; and the asterisks and open circles are values that fall more than 1.5 and 3 inter-quartile ranges from the hinges, respectively. The medians of logarithms differ slightly from the logarithms of medians in Figs. 3 and 4. The range of the left vertical scale is one order of magnitude larger for Asia than for the Americas and Africa.

their buffers. This is not true for sharp environmental gradients associated with topographic relief. When a reserve includes an isolated ridge, mountain, or volcano surrounded by relatively level terrain, orographic rainfall could decrease flammability and increased cloud cover could decrease fire detectability in the reserve relative to the surrounding buffer area located on relatively level terrain. Thus, buffer : reserve fire detec-

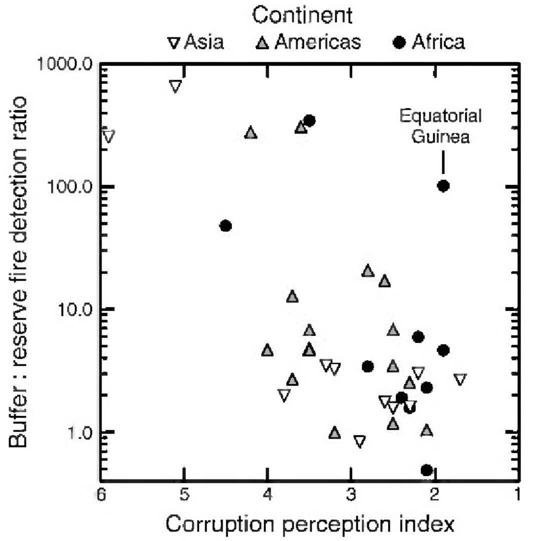

FIG. 3. The linear relationship ($r^2 = 0.37$, $P < 0.001$) between the median buffer : reserve fire detection ratio for moist forest reserves in the 37 countries depicted in Fig. 2 (note log scale) and the corruption perception index (CPI). The horizontal scale is reversed because the CPI takes values near 1 for the most corrupt countries and values near 10 for the least corrupt countries (Poroznuk 2005). Two data points were moved slightly to become visible.

tion ratios might be biased toward larger values where topographic relief is large inside reserves and low in the contiguous buffer area.

Despite this caveat, we believe this study provides strong evidence that most tropical moist forest reserves are at least partially effective at reducing fire incidence. This evidence comes from a highly significant reduction in fire detections relative to contiguous, unprotected buffer areas for 823 reserves from across the tropics and subtropics (Fig. 1). Similarly, reserve status reduced grazing, hunting, fire, timber extraction, and forest clearing for 60–97% of reserves threatened by these activities in a questionnaire-based study of 93 reserves from 22 tropical countries (Bruner et al. 2001). Likewise, forest clearing occurred in 25% of reserves but in 70% of their 50-km buffer areas in a satellite-based remote sensing study of 198 reserves scattered widely across the tropics (DeFries et al. 2005). This study, Bruner et al. (2001) and DeFries et al. (2005) all point toward the hopeful conclusion that tropical reserves tend to be at least partially effective.

The buffer : reserve fire detection ratio provides additional insight into the effectiveness of moist forest reserves, but must be interpreted cautiously. Large values presumably indicate that humans have increased fire frequency just outside reserves and that reserve status effectively reduces these activities. Small values approaching one might occur under two contrasting scenarios. The number of fires might be very high everywhere, which would indicate that a moist forest reserve was in dire trouble. Alternatively, the number of fires might be very low everywhere. This last scenario is consistent with passive protection through isolation from humans and also with effective reserves surrounded by human-dominated landscapes where fire frequency is also low. There are many examples of human-dominated landscapes with low fire frequency in the tropics including coffee, cacao, and rice producing areas. For these reasons, we will use fire detection densities inside reserves to help interpret the buffer : reserve ratio.

Costa Rica, Jamaica, Malaysia, and Taiwan have the most effective moist forest reserves with respect to fire incidence. Fire detection densities approach zero inside their moist forest reserves, and the median buffer : reserve ratio exceeds 200 (Fig. 2). This level of success sets a standard that should be achievable elsewhere. These four countries are, however, among the wealthiest and least corrupt third of the 37 countries considered here and share a long history of political stability. This brings us to reasons for grave concern.

Fire detections provide less evidence that tropical moist forest reserves are effective in many poorer countries and in countries beset by corruption (Figs. 3 and 4). Changes in total forest cover showed similar relationships with poverty and corruption in a multiple regression analysis that included a wide range of developed and developing countries (Smith et al. 2003*b*). Our analyses extend these findings to include the effectiveness of forest reserves and demonstrate that the relationships hold over the restricted subset of values of the corruption perception and human development indices observed among developing tropical and subtropical countries (Figs. 3 and 4).

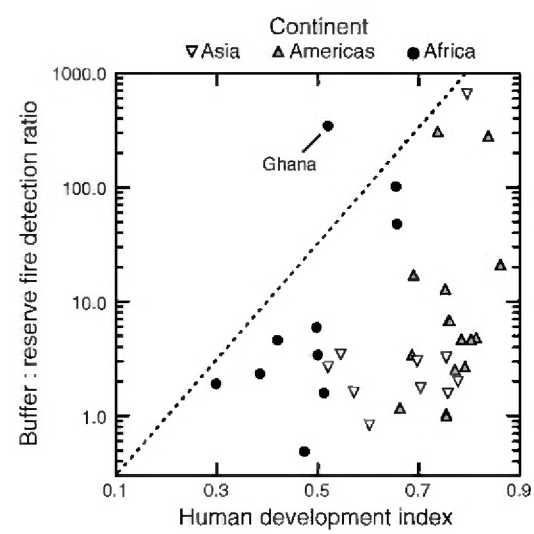

FIG. 4. The triangular relationship between the median buffer : reserve fire detection ratio for moist forest reserves in the 37 countries depicted in Fig. 2 (note log scale) and the human development index. The human development index ranges from a low of 0.281 for Niger to a high of 0.963 for Norway (UNDP 2005). The arbitrary dashed line highlights the triangular relationship with Ghana as the sole exception.

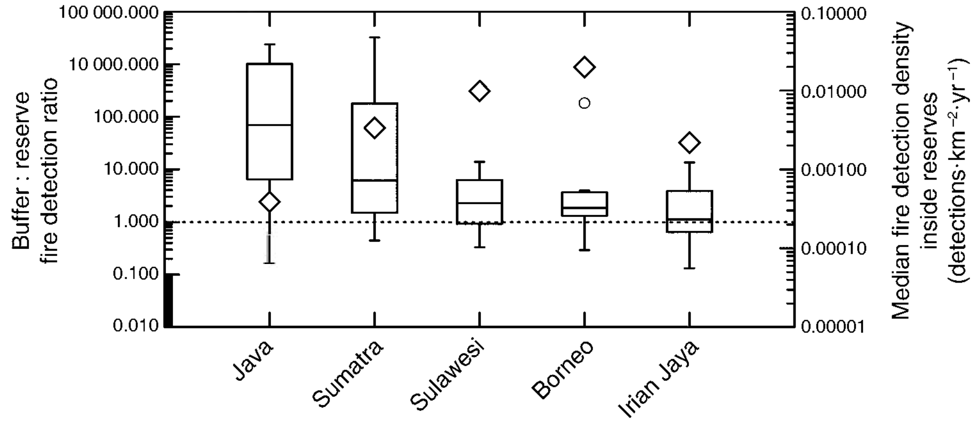

FIG. 5. The buffer : reserve fire detection ratio (box plots, left vertical scale) and median fire detection density inside reserves (open diamonds, right vertical scale) for tropical moist forest reserves from the five principal Indonesian islands. Values are for 10, 31, 11, 16, and 7 reserves for Java, Sumatra, Sulawesi, Borneo, and Irian Jaya, respectively. The legend to Fig. 2 provides further explanation. Note the log scales.

We are able to identify four countries where many moist forest reserves are failing to prevent fire today. Median fire detection densities approach one per 10 square kilometers per year inside moist forest reserves in Cambodia, Guatemala, Paraguay, and Sierra Leone, and median buffer : reserve fire detection ratios are just 1.6, 1.2, 1.0, and 1.9, respectively (Fig. 2). Paraguay had the second highest perceived level of corruption in the Americas after Haiti (Poroznuk 2005) and the highest 1990s deforestation rate in the world (Hansen and DeFries 2004). Cambodia suffered civil war punctuated by genocide from 1970 until the Khmer Rouge surrendered in 1999. Guatemala suffered civil war from 1960 until a 1996 peace treaty. Sierra Leone suffered civil war, genocide, and the displacement of up to one-third of its population between 1991 and 2002. Political instability, corruption, and poverty compromise the effectiveness of moist forest reserves in these four countries.

Another five countries (Suriname, the Congo, Kenya, the Philippines, and India) have median buffer : reserve fire detection ratios <2 (Fig. 2). For Kenya and India, fire detection densities actually tend to be greater inside moist forest reserves than in contiguous buffer areas (median buffer : reserve fire detection ratios <1, Fig. 2). This is also the case in the Mexican state of Chiapas (Román-Cuesta and Martínez-Vilalta 2006) and is likely to reflect intensive land use that prevents fires in buffer areas, a lack of fuel to sustain fires in buffer areas, intense human pressure on reserves, and ample fuel to sustain fires inside reserves.

The situation is very different in the Congo and Suriname. Here median fire detection densities are less than one per 10 000 square kilometers per year inside moist forest reserves and are similarly low inside contiguous buffer areas (Fig. 2). Reserves appear to benefit from passive protection through isolation from human activities that increase fire frequency. Other countries where low fire detection densities inside moist forest reserves and contiguous buffer areas suggest that passive protection is important include Cameroon and remote reserves in Amazonian Brazil, Colombia, Ecuador, and Peru (Fig. 2; Nepstad et al. 2006).

The reserves of Indonesian Borneo have recently suffered severe levels of timber extraction and forest clearing facilitated by corruption (Smith et al. 2003*a*, Curran et al. 2004). The 81 Indonesian moist forest reserves permit analyses for the five principal Indonesian islands (Fig. 5). Fire detections indicate that the crisis in Borneo is nearly as severe as ongoing crises in Cambodia, Guatemala, Paraguay, and Sierra Leone (Figs. 2 and 5). In stark contrast, the reserves of Java appear to be among the most effective in the tropics with relatively low fire detection densities inside and nearly 100-fold greater fire detection densities in contiguous buffer areas. Finally, the reserves of Irian Jaya appear to benefit from passive protection through isolation with similar low fire detection densities both inside reserves and their buffer areas (Fig. 5). The Indonesian example brings us to what is perhaps the most salient finding of this study.

Tropical moist forest reserves vary wildly in their effectiveness to reduce fires. Fire detection density varies by more than five orders of magnitude among 823 tropical moist forest reserves (Fig. 1). The impact of reserve status on fire detections varies by up to four orders of magnitude among reserves within a single country (Fig. 2) and even among reserves within a small portion of a single country (Fig. 5). We urgently need to understand the causes of this variation so that steps can be taken to improve the effectiveness of all tropical forest reserves. The Supplement that accompanies this article provides fire detection densities for 3964 tropical and subtropical reserves listed in the WDPA and for their 5-, 10-, and 15-km buffer areas. We hope these data will facilitate national, regional, and further global level analyses and generate new insights to improve the success of tropical forest reserves. In the meantime, increases in staff and funding are already known to improve the effectiveness of tropical reserves (Bruner et al. 2001, Terborgh et al. 2002). New resources to improve the effectiveness of forest reserves are urgently needed in many poor tropical countries and especially in Cambodia, Guatemala, Paraguay, and Sierra Leone.

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SUPPLEMENT

Fire detections in tropical reserves and their buffer areas (*Ecological Archives* A017-047-S1).