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Global evidence that deforestation amplifies flood risk and severity in the developing world

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Abstract

With the wide acceptance of forest-protection policies in the developing world comes a requirement for clear demonstrations of how deforestation may erode human well-being and economies. For centuries, it has been believed that forests provide protection against flooding. However, such claims have given rise to a heated polemic, and broad-scale quantitative evidence of the possible role of forests in flood protection has not been forthcoming. Using data collected from 1990 to 2000 from 56 developing countries, we show using generalized linear and mixed-effects models contrasted with information-theoretic measures of parsimony that flood frequency is negatively correlated with the amount of remaining natural forest and positively correlated with natural forest area loss (after controlling for rainfall, slope and degraded landscape area). The most parsimonious models accounted for over 65% of the variation in flood frequency, of which nearly 14% was due to forest cover variables alone. During the decade investigated, nearly 100 000 people were killed and 320 million people were displaced by floods, with total reported economic damages exceeding US$1151 billion. Extracted measures of flood severity (flood duration, people killed and displaced, and total damage) showed some weaker, albeit detectable correlations to natural forest cover and loss. Based on an arbitrary decrease in natural forest area of 10%, the model-averaged prediction of flood frequency increased between 4% and 28% among the countries modeled. Using the same hypothetical decline in natural forest area resulted in a 4–8% increase in total flood duration. These correlations suggest that global-scale patterns in mean forest trends across countries are meaningful with respect to flood dynamics. Unabated loss of forests may increase or exacerbate the number of flood-related disasters, negatively impact millions of poor people, and inflict trillions of dollars in damage in disadvantaged economies over the coming decades. This first global-scale empirical demonstration that forests are correlated with flood risk and severity in developing countries reinforces the imperative for large-scale forest protection to protect human welfare, and suggests that reforestation may help to reduce the frequency and severity of flood-related catastrophes.

Keywords: conservation, damage, flooding events, forest loss, generalized linear mixed-effects models, generalized linear models, human displacement, projected costs, rainfall

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Introduction

With the alarming loss of natural habitats around much of the world (Kerr & Currie, 1995; Laurance, 1999; Achard *et al.*, 2002; Balmford *et al.*, 2003; Brook *et al.*, 2003), humanity is being robbed of essential ecosystem services such as air purification, weather regulation, maintenance of soil fertility and stability, waste detoxification and pest control (Daily, 1997; Laurance & Williamson, 2001; Chivian, 2002; Díaz *et al*., 2006; Vittor *et al*., 2006). Economic losses through the degradation of natural services have been used to argue for the imperative of conservation (Balmford *et al*., 2002; Ricketts *et al*., 2004), but only to a limited extent. As such, for conservation to receive wide political and popular attention and priority, especially in the developing world, there needs to be empirical evidence of nature's role in supporting human well-being. For example, research can test the degree to which the loss of natural habitats drives disasters that disrupt human lives and property (Kar & Kar, 1999). This is most urgent in developing nations where the highest levels of biotic endemism are generally found (Myers *et al*., 2000), rates of natural habitat loss are disproportionately high (Laurance, 1999; Achard *et al*., 2002; Sodhi *et al*., 2007), and where, ironically, politicians and the populace generally remain apathetic toward the loss of natural habitats (Jepson, 2001) or do not see value in their conservation.

For centuries it has been vehemently claimed, and hotly disputed, that forests provide natural protection from floods (the rising of water bodies and their overflowing onto normally dry land) (Agarwal & Chak, 1991; Blaikie & Muldavin, 2004; Bruijnzeel, 2004; FAO & CIFOR, 2005; Calder & Aylward, 2006). Each year, extreme floods kill and displace hundreds of thousands of people and result in billions of dollars in damages to property and infrastructure, particularly in developing countries with large rural and agrarian populations (FAO & CIFOR, 2005; Jonkman, 2005). Despite considerable variation in the interrelated conditions impinging on flood formation, such as geological composition, terrain slope, soil permeability, porosity, crusting and prior wetness, and incident rainfall intensity and duration (Reed, 2002), there is some evidence that forest loss imposes an additional vulnerability on landscapes to floods; at least in certain circumstances (Clark, 1987; Bruijnzeel, 1990, 2004). The proposed mechanism is that loss of vegetation can lead to increased runoff due to reductions in the interception of rainfall and the evaporation of water from the tree canopy, coupled with reductions in the hydraulic conductivity (infiltration rate) of soils (Clark, 1987). Thus, the high rate at which forests are currently being lost (Laurance, 1999; Achard *et al*., 2002) has led to the hypothesis that natural habitat loss increases the risk and severity of extreme floods and their associated cost to human life and property (Clark, 1987). Yet, because the claim lacks broad-scale empirical support, the development and implementation of clear flood-mitigation policies regularly stall (FAO & CIFOR, 2005; Calder & Aylward, 2006).

Here, we provide the first global-scale evidence that the amount of remaining natural forest cover and the rate of its loss are correlated with flood risk and severity in developing countries where such disasters have and will continue to impact human well-being and suppress economic prosperity. We used data collected between 1990 and 2000, from 56 developing countries in Africa, Asia and Central/South America, to determine the role of forests in mediating flood dynamics. We tested two general, but linked hypotheses: (i) that flooding frequency (risk) increases as natural forest cover decreases and (ii) that severity (measured as total flood duration, the number of people killed or displaced, and infrastructure damage) associated with floods is higher when natural forest cover is lower.

Materials and methods

Flood frequency

There is a considerable body of literature devoted to the development of complex, catchment-specific models to predict the temporal frequency of floods (Cameron *et al*., 2000; Arnaud & Lavabre, 2002; Cunderlik & Burn, 2002; Prudhomme *et al*., 2002); however, no attempts have been made to predict flood frequency over broader spatial scales. As such, we investigated global patterns of flood frequency using the country as the unit of investigation because: (i) we postulate that only over broad spatial scales will general patterns emerge and (ii) too few data at the global scale exist for within-country (i.e. catchment level) model designs.

Our first aim was, therefore, to test the hypothesis that a country's flood frequency increases as its forest cover decreases. This can be examined in two ways: (i) flood frequency is correlated with the total forest cover (natural and plantation) and/or (ii) flood frequency is correlated with the total forest cover loss over the period of interest. The dependent variable (flood frequency) was the frequency of flooding events (number of floods observed between 1990 and 2000), extracted from remotely sensed flood data from the Dartmouth Flood Observatory (www.dartmouth.edu/~floods/index.html). The Flood Observatory uses a collection of tools [e.g. MODIS (Moderate Resolution Imaging Spectroradiometer, http://modis.gsfc.nasa.gov) optical remote sensing, which provides frequent updates of surface water condition worldwide] to detect and locate river flood events. The minimum flood size recorded was 4–5 ha. Only floods caused by heavy or brief torrential rain were included; those caused by typhoons, cyclones, dam breakage and tsunamis were excluded because they represent events that originate independently of landscape characteristics (although the magnitude of their impact may be subsequently influenced by them). The average flood sizes in terms of area affected ranged from 1170 to 78 900 km^2.

The explanatory variables considered were: (i) the mean cover of natural forest from 1990 to 2000 and (ii) the annual loss of natural forest cover between 1990 and 2000 (Fig. 1). Data on natural forest cover and natural forest loss during the same period were obtained from the World Resources Institute (www.wri.org, Earthtrends Forests, Grasslands and Drylands data tables), which bases much of its compiled datasets on information provided by the Food and Agricultural Organization (FAO, www.fao.org). The area of each country was obtained from the FAO databases (www.fao.org). However, a simple comparison of flood frequency and forest cover/loss at the global scale is unfeasible given the large number of confounding variables that will potentially influence the number of floods a particular country experiences. As such, a number of 'control' variables were considered in the model structure (see below for methods and statistical details) in an attempt to determine the contribution of forest cover/loss to flood frequency above and beyond the average climatic, landscape and soil characteristics particular to each country. For these reasons, we also collected information on average total annual precipitation, an index of average steepness (slope), major soil moisture regime and area of degraded land (see details below).

It is well known that climate variation affects flood risk and frequency through the modification of rainfall intensity and pattern (Franks & Kuczera, 2002; Muzik, 2002; Kiem *et al*., 2003). Indeed, the principal flood-generating factor is rainfall intensity and duration within a catchment's boundary (Reed, 2002). We therefore included a coarse index of spatial variation in precipitation for the countries investigated that was derived from the WorldClim global climate grids (www.worldclim.org). We used the 5 arc-minute resolution of the annual precipitation (mm) grid describing mean values from 1960 to 1990 (Hijmans *et al*., 2005) (Fig. 2). For each country, we extracted the corresponding precipitation averages and calculated a country's median value because of the typically skewed distribution of precipitation over an entire country's surface.

Another potential control variable influencing the spatial variation in flood frequency among countries is the average 'ruggedness,' or 'steepness,' of the terrain, which governs the residence time of water and the speed of baseflow recession (Ward & Robinson, 1990; Reed, 2002). We calculated an index of steepness as the mean elevation gradient (or 'slope,' at 0.5° resolution) for each country (Fig. 2) from the International Satellite Land-Surface Climatology Project, Initiative II Data Archive (Hall *et al*., 2005).

The type of postforest land cover can have a large hydrological impact in tropical catchments (Bruijnzeel, 2004). Increases in urbanization, area under heavy grazing pressure and intensive annual cropping can all lead to large changes in water flow patterns (Costa *et al*., 2003; Bruijnzeel, 2004). We therefore collected data on the total 'degraded' area of each country devoted to urbanization, cropland and cropland/natural vegetation mosaic from the Global Land Cover Characteristics Database (GLCCD) (Loveland *et al*., 2000). 'Urbanization' was defined as the area covered by buildings and other man-made structures; 'croplands' were defined as lands covered with temporary crops followed by harvest and a bare soil period; cropland/natural vegetation mosaics consist of croplands, forests, shrublands and grasslands in which no one component comprises more than 60% of the landscape (Loveland *et al*., 2000).

The underlying soil moisture regime can have profound effects on the frequency and severity of flooding; for example, relatively small amounts of water accumulation from rainfall in an arid region can lead to temporary flash flooding, whereas an equivalent amount of rain falling on perhumid soils may not result in any particularly noticeable accumulation of surface water (Beljaars *et al*., 1996; Cassardo *et al*., 2002). Therefore, we also considered antecedent soil moisture regime of each country based on the world Soil Moisture Regimes Map (Natural Resources Conservation Service, 1997). For each country considered we classified the dominant (the largest area class within that country) soil moisture regime as: (1) arid/semi-arid when the regime was aridic (limiting plant growth during much of the growing season) or xeric (deficient in available moisture for the support of life); (2) subhumid when the regime was ustic (characterized by limited moisture during most of the year but with at least one rainy season of $\geq$3 months' duration when the soil is moist); or (3) perhumid when the regime was udic (the soil is not dry for as long as 90 cumulative days) or perudic (rainfall exceeds evapotranspiration throughout the year and the soil never dries completely) (Natural Resources Conservation Service, 1997). Raw data are presented in Tables A1 and A2.

Flood severity

The frequency of flooding does not necessarily characterize the severity of the events in terms of their negative impacts on the landscape, human life and property. We therefore tested the relationships between forest area/deforestation and four measures of flood severity: (1) flood frequency weighted by the average duration of floods; (2) the number of people killed by flooding; (3) the number of people displaced by flood-

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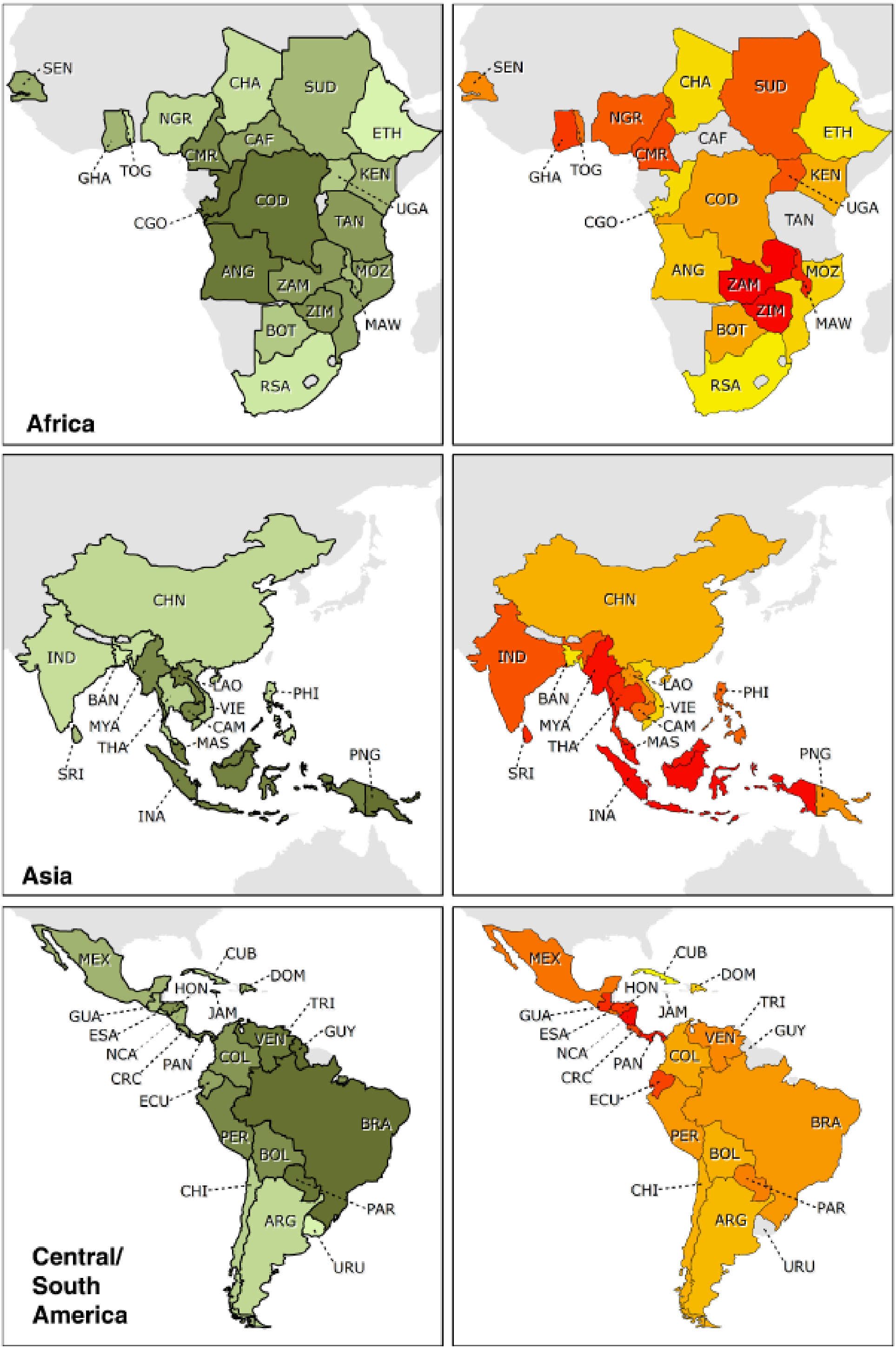
ing; and (4) the total economic damage done by flooding. The Flood Observatory database provides the average duration of all floods occurring between 1990 and 2000, as well as the average area flooded. However, the latter data (area flooded) were missing for 25 countries, so we only weighted the number of floods by their average duration (in days) as the response variable.

The Flood Observatory database also provides the number of people killed or displaced over the period of 1990–2000, as well as the infrastructure damage (mean estimated cost in $US) attributed to floods during that



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period. However, some flood statistics were unavailable for certain floods, so we calculated the average severity values per country and multiplied these by the flood frequency to obtain approximate total values. Thus, our next hypothesis was that the number of people affected, and damage done by extreme floods, increases as natural forest cover decreases. In the case of the total damage done by floods, the total gross damage (in $US) is potentially confounded by variation in the local cost of living (economic prosperity) among countries. To control for this, we also considered the total gross damage corrected for purchasing power parity (PPP) as a damage response variable. PPP equalizes the costs among countries in terms of their purchasing power and standards of living (www.worldbank.org). To obtain PPP correction data, we accessed the World Bank website and obtained the 2002 Gross National Income (GNI) and the PPP-adjusted GNI (PPP-GNI) for each country (http://siteresources.worldbank.org/ICPINT/Resources/Table1_1.pdf). The PPP conversion factor was expressed simply as the ratio of PPP-GNI to GNI, and this was applied to the total damage figures and the analysis repeated.

All control and explanatory variables described above for the relationships to flood frequency were used for the severity responses, with the addition of the estimated human population size for each country (i.e. additional control variable). Mean human population sizes for 1999 were obtained from the Food and Agricultural Organization databases (www.fao.org). Some data were not available for all countries, so sample sizes vary depending on the severity response variable used in analysis. Raw data are presented in Tables A1 and A2.

Statistical analyses

Given the probable complexity of the relationship between flood frequency and severity and the hypothesized correlates, simple linear multiple regression and stepwise model building were considered inappropriate (Whittingham *et al*., 2006). We instead used a multimodel, inferential approach based on information theory (Burnham & Anderson, 2002) to construct a limited *a priori* model set to examine our major hypotheses. Our model building strategy was based on the following logic:

(1) The number of floods experienced in any one country should depend on the total area of the country (i.e. more area = higher total frequency), the average rainfall it receives, the average gradient (slope), and the amount of degraded land (the sum of the area devoted to urbanization, cropland and cropland/natural vegetation mosaic). As such, all models considered these four covariates as 'control' variables (flood frequency and forest cover values were not first divided by country area to avoid spurious positive correlations) (Jackson & Somers, 1991);

(2) The antecedent soil moisture regime of a given country was considered as a random factor (arid/semiarid, subhumid or perhumid) for all models considered (see model structure below);

(3) We reasoned that natural forest area (in 2000) and natural forest loss (between 1990 and 2000) would not influence flood frequency in a mutually exclusive fashion considering the 'natural' condition of a country may have varying forest coverage for reasons independent of human deforestation activities; therefore, both were considered simultaneously in certain models, with an interaction between them considered plausible given that flood frequency may also depend on the amount of forest loss relative to the initial state;

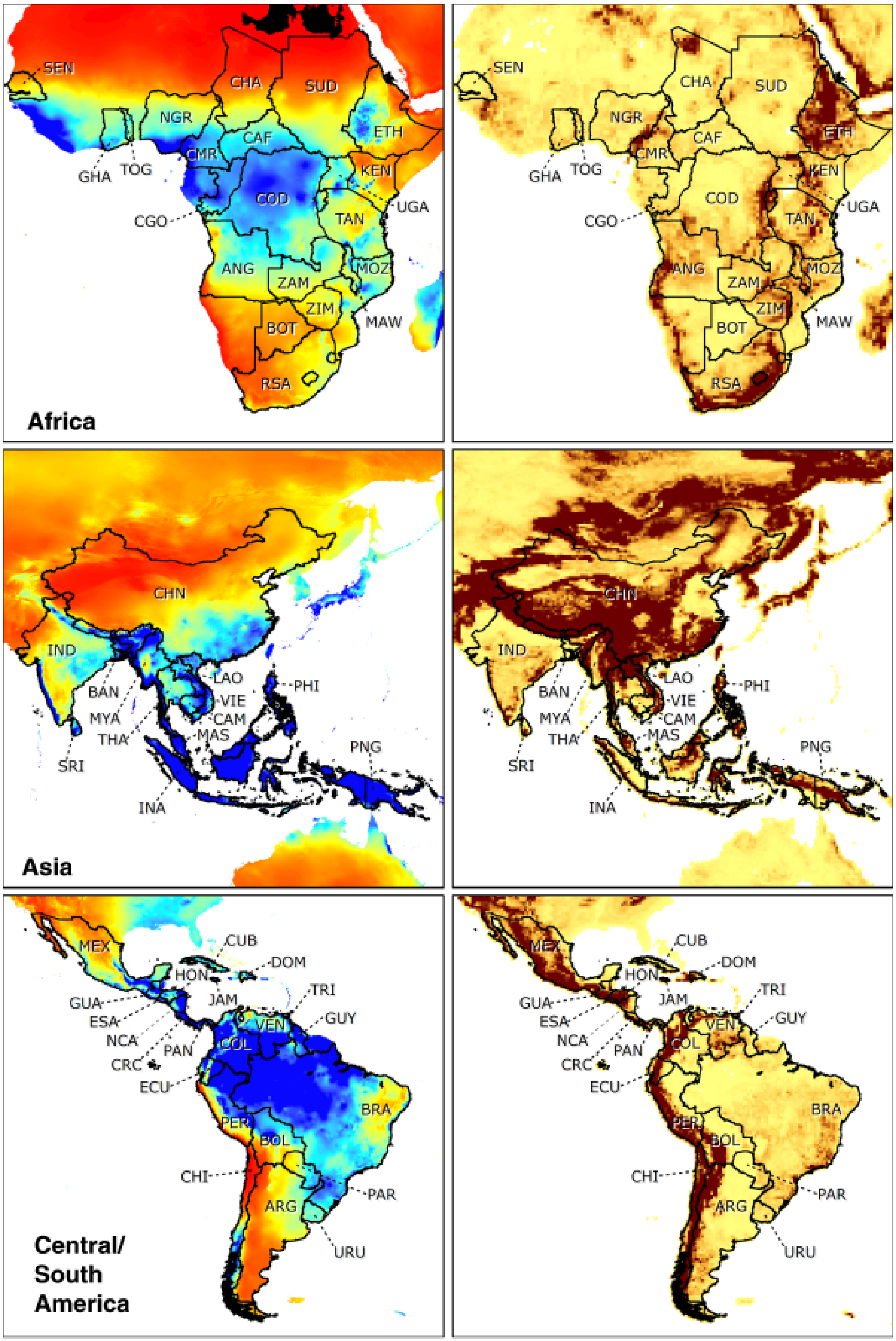
(4) Natural and total forest cover are highly correlated (data not shown), but the difference ['nonnatural' (plantation or nonnative) vegetation] may explain some additional variance in flood frequency given that nonnative forest cover may not always affect water yields in the same manner as native vegetation (Bruijnzeel, 2004);

(5) Finally, we hypothesized two other potential interactions between slope and natural forest cover and between slope and natural forest loss; the former because countries with higher gradients may experience more floods regardless of their forest cover; the latter

Fig. 1 Left panels: Proportion of total natural forest cover (total natural forest cover ÷ total area; 2000 values) for the countries examined in Africa, Asia and Central/South America. Scale colors represent lowest (lighter) to highest (darker) proportions. Right panels: Proportion of total forest loss between 1990 and 2000 (total forest loss ÷ total area). Scale colours represent lowest (lighter) to highest (darker) proportions (missing values for CAF, GUY, JAM, TAN, TRI). Country abbreviations: ANG, Angola; BOT, Botswana; CMR, Cameroon; CAF, Central African Republic; CHA, Chad; CGO, Congo; CDO, Democratic Republic of Congo; ETH, Ethiopia; GHA, Ghana; KEN, Kenya; MAW, Malawi; MOZ, Mozambique; NGR, Nigeria; RSA, Republic of South Africa; SEN, Senegal; SUD, Sudan; TAN, Tanzania; TOG, Togo; UGA, Uganda; ZAM, Zambia; ZIM, Zimbabwe; BAN, Bangladesh; CAM, Cambodia; CHN, China; IND, India; INA, Indonesia; LAO, Laos; MAS, Malaysia; MYA, Myanmar; PHI, Philippines; PNG, Papua New Guinea; SRI, Sri Lanka; THA, Thailand; VIE, Vietnam; ARG, Argentina; BOL, Bolivia; BRA, Brazil; CHI, Chile; COL, Colombia; CRC, Costa Rica; CUB, Cuba; DOM, Dominican Republic; ECU, Ecuador; ESA, El Salvador; GUA, Guatemala; GUY, Guyana; HON, Honduras; JAM, Jamaica; MEX, Mexico; NCA, Nicaragua; PAN, Panama; PAR, Paraguay; PER, Peru; TRI, Trinidad & Tobago; URU, Uruguay; VEN, Venezuela.

because high- (or low-) gradient countries experiencing heavy forest loss may have even more frequent flooding than either variable could predict additively (i.e. a multiplicative effect). Model sets are presented in Table 1. We further reasoned that the relatively low sample size (56 countries) necessitated an analysis considering no more than 10 models per response variable. In the case of the number of people killed or displaced and the total damage done by floods, we added the fifth 'control' variable, human population size, to control for per capita effects.

We used a generalized linear mixed-effect model (GLMM) structure, implemented using the `lmer` function in the R Package (R Development Core Team, 2004).



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The random effects structure corrects for nonindependence of statistical units (countries) due to similar antecedent soil moisture regimes. All other variables were coded as fixed effects. The flood frequency response variable was square-root transformed, and all predictor variables were log-transformed before analysis to control for the extremely non-Gaussian distributions. For flood frequency, we used a Gaussian error structure and set the link function to a square-root to account for remaining deviation from normality and homoscedascticity. All other analyses used a Gaussian error structure and identity link function. We also examined each model set using generalized linear models (GLM) in addition to GLLMs to examine the influence of the random effect of antecedent soil moisture regime (function `glm` in the R Package).

An index of Kullback–Leibler (K-L) information loss was used to assign relative strengths of evidence to the different competing models (Burnham & Anderson, 2002), and Akaike's information criterion (AIC_c) was used as the method to compare relative model support given that it corrects for small sample sizes (all n in this study were <55) (Burnham & Anderson, 2002). One could also use other methods to compare models such as the dimension-consistent Bayesian information criterion (BIC); however, BIC may only be preferable when sample sizes are large (Burnham & Anderson, 2004; Link & Barker, 2006). The relative likelihoods of candidate models were calculated using AIC_c (Burnham and Anderson, 2002), with the weight ($wAIC_c$) of any particular model varying from 0 (no support) to 1 (complete support) relative to the entire model set. For each model considered, we also calculated the percentage deviance explained (%DE) as a measure of goodness-of-fit, and compared each model's %DE with that of the control model to examine what proportion of the variance in the response was attributable to the forest cover variables.

We predicted the model-averaged flood frequency for each country (i.e. sum of the predicted frequencies for each model multiplied by the model's AIC_c weight) using the `predict.glm` function in the R Package (i.e.

Table 1 The *a priori* model set used to examine the relationship between the flood frequency and severity response variables using generalized linear modelling

Model no.	Model	Analytical theme
1	$Response \sim AR + RN + SL + DG + NFC + NFL + NNFC + NVC \times NFL + SL \times NFC + SL \times NFL$	Saturated + interactions
2	$Response \sim AR + RN + SL + DG + NFC + NFL + NNFC$	Saturated without interactions
3	$Response \sim AR + RN + SL + DG + NFC + NFL + NNFC + NVC \times NFL$	Saturated + forest cover × loss interaction
4	$Response \sim AR + RN + SL + DG + NFC + NFL + NNFC + SL \times NFC$	Saturated + slope × forest cover interaction
5	$Response \sim AR + RN + SL + DG + NFC + NFL + NNFC + SL \times NFL$	Saturated + slope × forest loss interaction
6	$Response \sim AR + RN + SL + DG + NFC + NNFC$	Saturated without forest loss
7	$Response \sim AR + RN + SL + DG + NFC + NFL$	Saturated without forest cover
8	$Response \sim AR + RN + SL + DG + NFC + NFL$	Saturated without nonnatural forest cover
9	$Response \sim AR + RN + SL + DG$	Control
10	$Response \sim 1$	Null

Shown are the term abbreviations (*AR*, country area; *RN*, median average annual precipitation; *SL*, average slope, *DG*, total degraded area; *NFC*, natural forest cover; *NFL*, natural forest loss; *NNFC*, nonnatural forest cover) and their interactions, as well as the major analytical (hypothesis) theme represented by each model.

Fig. 2 Left panels: Average annual precipitation for the period 1960–1990 derived from the WorldClim (www.worldclim.org) database at 5 arc-minute resolution (Hijmans *et al*., 2005) for the countries examined in Africa, Asia and Central/South America. Scale colours represent driest (red) to wettest (blue) conditions. Right panels: Mean elevation gradient (slope) at 0.5° resolution derived from the International Satellite Land-Surface Climatology Project, Initiative II Data Archive (Hall *et al*., 2005). Scale colours represent lowest (light yellow) to highest (dark brown) gradient. Country abbreviations: ANG, Angola; BOT, Botswana; CMR, Cameroon; CAF, Central African Republic; CHA, Chad; CGO, Congo; CDO, Democratic Republic of Congo; ETH, Ethiopia; GHA, Ghana; KEN, Kenya; MAW, Malawi; MOZ, Mozambique; NGR, Nigeria; RSA, Republic of South Africa; SEN, Senegal; SUD, Sudan; TAN, Tanzania; TOG, Togo; UGA, Uganda; ZAM, Zambia; ZIM, Zimbabwe; BAN, Bangladesh; CAM, Cambodia; CHN, China; IND, India; INA, Indonesia; LAO, Laos; MAS, Malaysia; MYA, Myanmar; PHI, Philippines; PNG, Papua New Guinea; SRI, Sri Lanka; THA, Thailand; VIE, Vietnam; ARG, Argentina; BOL, Bolivia; BRA, Brazil; CHI, Chile; COL, Colombia; CRC, Costa Rica; CUB, Cuba; DOM, Dominican Republic; ECU, Ecuador; ESA, El Salvador; GUA, Guatemala; GUY, Guyana; HON, Honduras; JAM, Jamaica; MEX, Mexico; NCA, Nicaragua; PAN, Panama; PAR, Paraguay; PER, Peru; TRI, Trinidad & Tobago; URU, Uruguay; VEN, Venezuela.

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Table 2 Generalized linear model results for the relationship between flood frequency (*FF*), the control variables (*AR*, country area; *RN*, median average annual precipitation; *SL*, average slope; *DG*, total degraded area) and forest cover attributes (*NFC*, natural forest cover; *NFL*, natural forest loss; *NNFC*, nonnatural forest cover) considered

Model	k	−LL	ΔAIC_c	$wAIC_c$	%DE	Δ%DE
$FF \sim AR + RN + SL + DG + NFC + NNFC$	8	−63.331	0.000	0.548	66.47	13.92
$FF \sim AR + RN + SL + DG + NFC + NFL + NNFC$	9	−62.679	1.684	0.236	67.33	14.78
$FF \sim AR + RN + SL + DG + NFC + NFL + NNFC + NFC \times NFL$	10	−62.452	4.372	0.062	67.62	15.07
$FF \sim AR + RN + SL + DG + NFC + NFL + NNFC + SL \times NFL$	10	−62.565	4.597	0.055	67.48	14.93
$FF \sim AR + RN + SL + DG + NFC + NFL + NNFC + SL \times NFC$	10	−62.665	4.798	0.050	67.35	14.80
$FF \sim AR + RN + SL + DG + NFL + NNFC$	8	−66.443	6.225	0.024	62.02	9.47
$FF \sim AR + RN + SL + DG + NFC + NFL$	8	−66.630	6.598	0.020	61.74	9.19
$FF \sim AR + RN + SL + DG + NFC + NFL + NNFC + NFC \times NFL + SL \times NFC + SL \times NFL$	12	−61.829	9.917	0.004	68.42	15.87
$FF \sim AR + RN + SL + DG$ (control model)	6	−72.009	11.797	0.002	52.55	—
$FF \sim 1$ (null model)	2	−90.646	39.374	<0.001	0.00	—

Shown for each model are the number of parameters (k), negative log-likelihood (−LL), change in Akaike's Information Criterion corrected for small sample sizes (ΔAIC_c), AIC_c weight ($wAIC_c$), the % deviance explained (%DE) in the flood frequency response variable and the absolute increase in %DE (Δ%DE) above the control model ($AR + RN + SL + DG$).

ignoring the weak random effect of antecedent soil moisture regime – see 'Results'). We then arbitrarily reduced each country's natural forest cover by 10% (and concomitantly added the residual to natural forest loss), and then recalculated the model-averaged predicted flood frequency for each country. We report the range of predicted percentage change in flood frequency and severity responses with this 10% additional loss of natural forest cover.

Results

Examination of the residual plots for all analyses identified several extreme outliers for China, so this country's values were removed from all analyses. The GLMM incorporating the antecedent soil moisture regime accounted for additional deviance in the responses relative to the simpler GLM by only a small (<1%) amount, so we only present the GLM results.

Flood frequency

The most highly ranked model ($wAIC_c = 0.548$) accounting for >66% of the deviance explained (Table 2) included all control variables (country area, rainfall, slope and degraded area) and natural forest cover (*NFC*) and nonnatural forest cover (*NNFC*). Flood frequency was positively correlated with all control variables, although the effect of slope was weakest (Fig. 3). Compared with the control model itself, the combined effects of *NFC* and *NNFC* explained an additional 13.9% of the deviance in flood frequency (Table 2), with flood frequency decreasing with increasing natural forest cover and increasing with nonnatural forest cover (Fig. 4a and b). The second-most highly ranked model included the natural forest loss (*NFL*) term ($wAIC_c = 0.236$) and accounted for an additional 0.9% of the deviance in flood frequency (Table 2). Examination of the partial residual plot of *NFL* vs. flood frequency also indicated a weakly positive relationship (Fig. 4c). The model-averaged predictions based on an additional hypothetical loss of natural forest cover of 10% resulted in a concomitant increase in predicted flood frequency ranging from 3.5% to 28.1% among the countries considered.

Flood severity

The relationship between each of the four flood severity response variables (flood duration, number of people killed, number of people displaced and PPP-adjusted damage) and the forest predictors was weaker than that for flood frequency (Table 3). As for flood frequency, flood duration was negatively correlated with natural forest cover, positively correlated with nonnatural forest cover, and only weakly positively correlated with natural forest loss (Fig. 5). The *NFC* and *NNFC* terms accounted for an additional 13.1% of the deviance in flood duration beyond that explained by the control variables (Table 3). A hypothetical 10% decrease in *NFC* resulted in a model-averaged predicted increase in flood duration ranging from 3.8% to 7.9%.

The correlations between the other severity measures and the forest predictors were weaker still, but there was evidence for relationships with some predictors

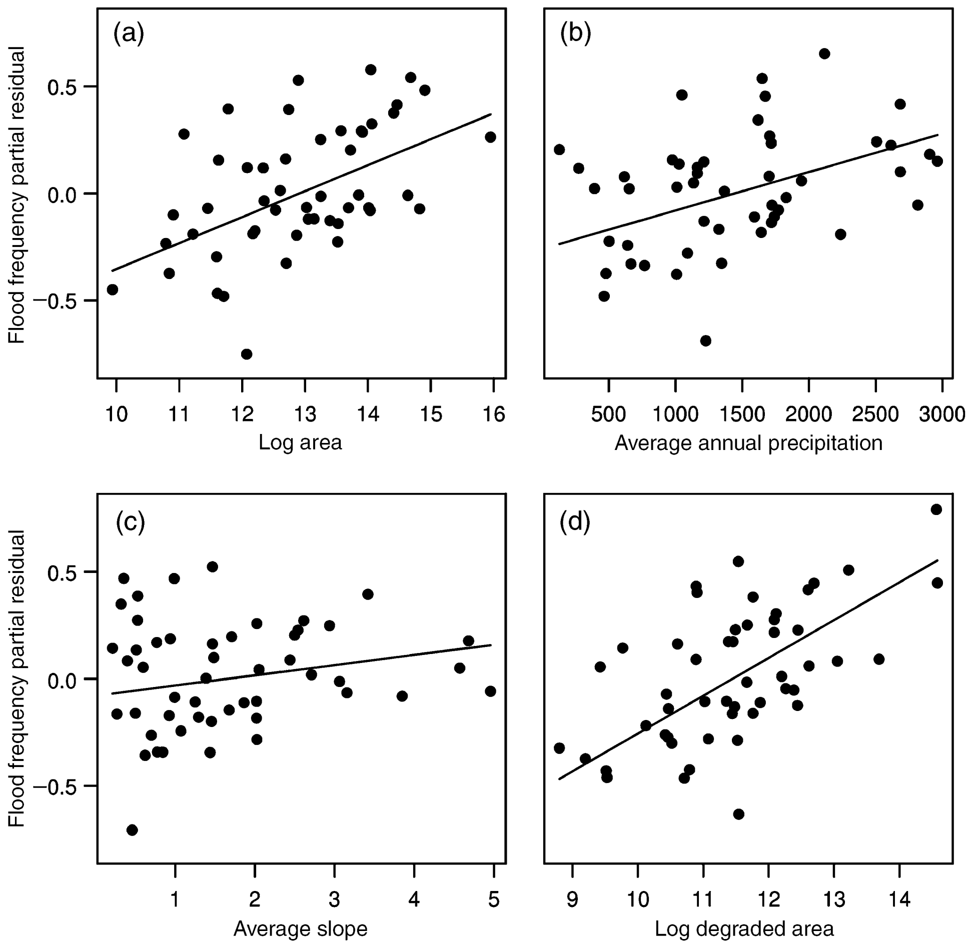

Fig. 3 Partial residual plots of flood frequency expressed as a function of the control variables from the model $FF \sim AR + RN + SL + DG + NFC + NNFC$ (see Tables 1 and 2): (a) log country area (km^2), (b) median average annual precipitation 1960–1990 (mm), (c) average slope (°) and (d) log area of degraded land (urban, cropland and cropland/natural vegetation mosaic).

Table 3 The two most highly ranked generalized linear model results for the relationships between each of the responses of flood duration (*FD*), people killed (*PK*), people displaced (*PD*) and damage (*DM*) and the control (*AR*, country area; *RN*, median average annual precipitation; *SL*, average slope; *DG*, total degraded area) and forest cover attributes (*NFC*, natural forest cover; *NFL*, natural forest loss; *NNFC*, nonnatural forest cover)

Model	k	−LL	ΔAIC$_c$	wAIC$_c$	%DE	Δ%DE
Flood duration						
$FD \sim AR + RN + SL + DG + NFC + NNFC$	8	−68.171	0.000	0.539	45.53	13.06
$FD \sim AR + RN + SL + DG + NFC + NFL + NNFC$	9	−68.074	2.795	0.133	45.74	13.27
People killed						
$PK \sim AR + RN + SL + DG$ (control model)	7	−89.902	0.000	0.810	42.26	—
$PK \sim AR + RN + SL + DG + NFC + NNFC$	9	−89.410	5.131	0.062	43.51	1.25
People displaced						
$PD \sim AR + RN + SL + DG$ (control model)	7	−99.326	0.000	0.825	44.33	—
$PD \sim AR + RN + SL + DG + NFC + NFL$	9	−99.004	5.348	0.057	45.09	0.76
Damage						
$DM \sim AR + RN + SL + DG$ (control model)	7	−45.544	0.000	0.859	60.14	—
$DM \sim AR + RN + SL + DG + NFL + NNFC$	9	−43.796	5.197	0.064	64.99	4.85

Shown for each model are the number of parameters (k), negative log-likelihood (−LL), change in Akaike's Information Criterion corrected for small sample sizes (ΔAIC$_c$), AIC$_c$ weight (wAIC$_c$), the % deviance explained (%DE) in the flood risk and severity response variables and the absolute increase in %DE (Δ%DE) above the control model ($AR + RN + SL + DG$).

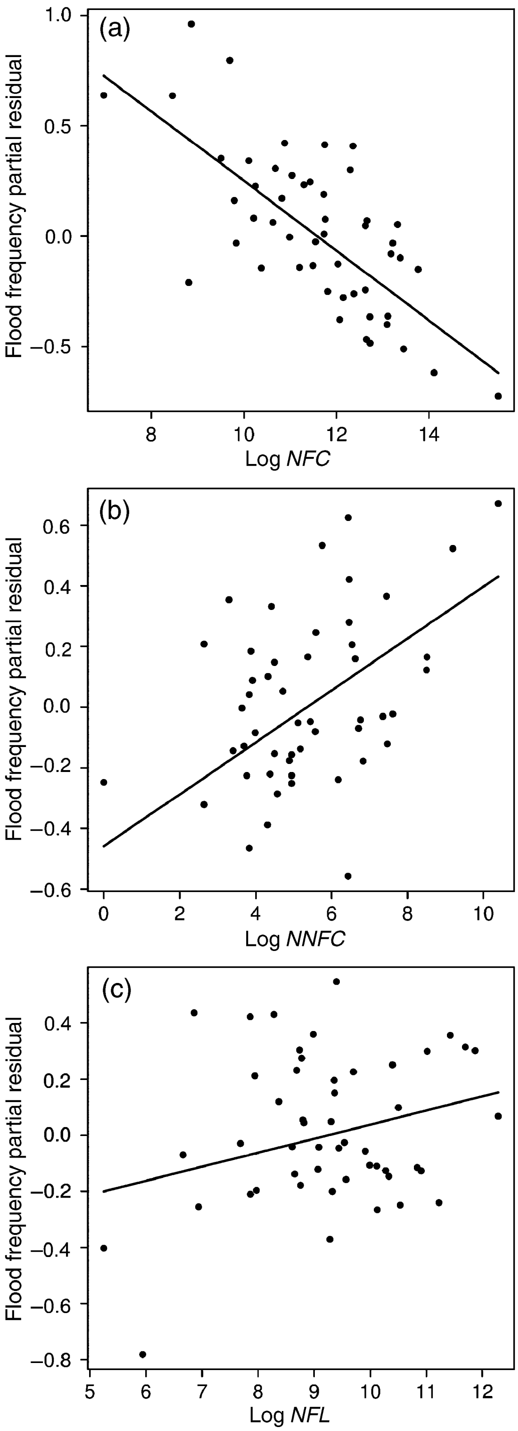

Fig. 4 Partial residual plots of flood frequency expressed as a function of the forest cover/loss metrics: (a) log natural forest cover (*NFC*, km^2), (b) log nonnatural forest cover (*NNFC*, km^2) and (c) natural forest loss between 1990 and 2000 (*NFL*, km^2) derived from the models $FF \sim AR + RN + SL + DG + NFC + NNFC$ and $FF \sim AR + RN + SL + DG + NFC + NFL + NNFC$ (see Tables 1 and 2).

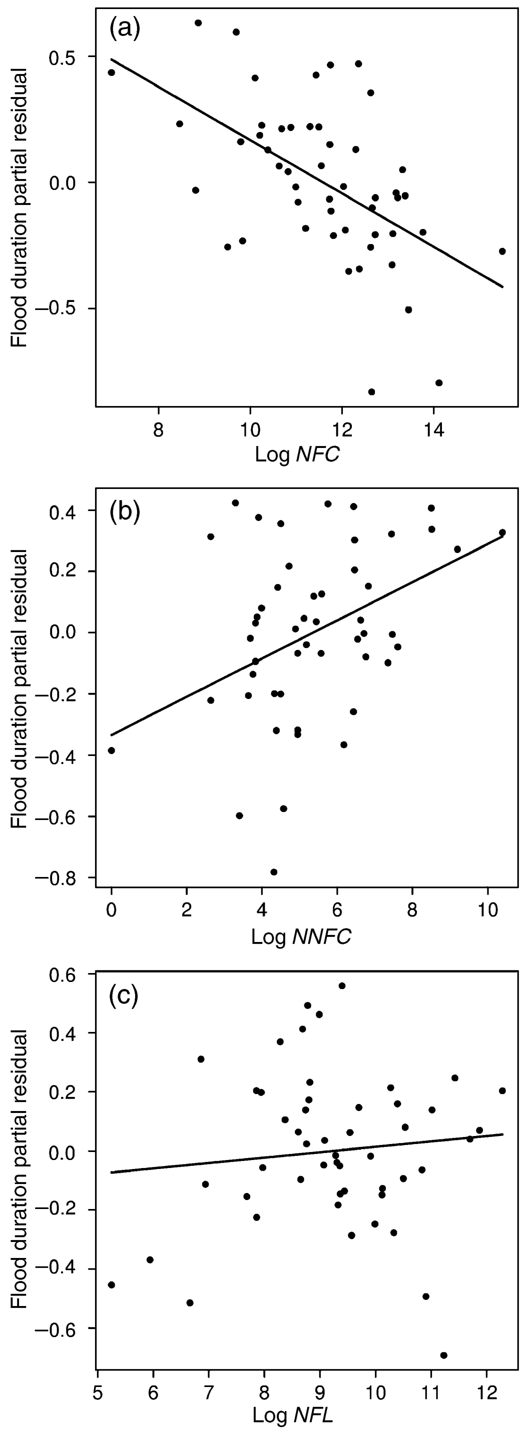

Fig. 5 Partial residual plots of flood duration expressed as a function of the forest cover/loss metrics: (a) log natural forest cover (*NFC*, km^2), (b) log nonnatural forest cover (*NNFC*, km^2) and (c) natural forest loss between 1990 and 2000 (*NFL*, km^2) derived from the models $FD \sim AR + RN + SL + DG + NFC + NNFC$ and $FD \sim AR + RN + SL + DG + NFC + NFL + NNFC$ (see Tables 1 and 3).

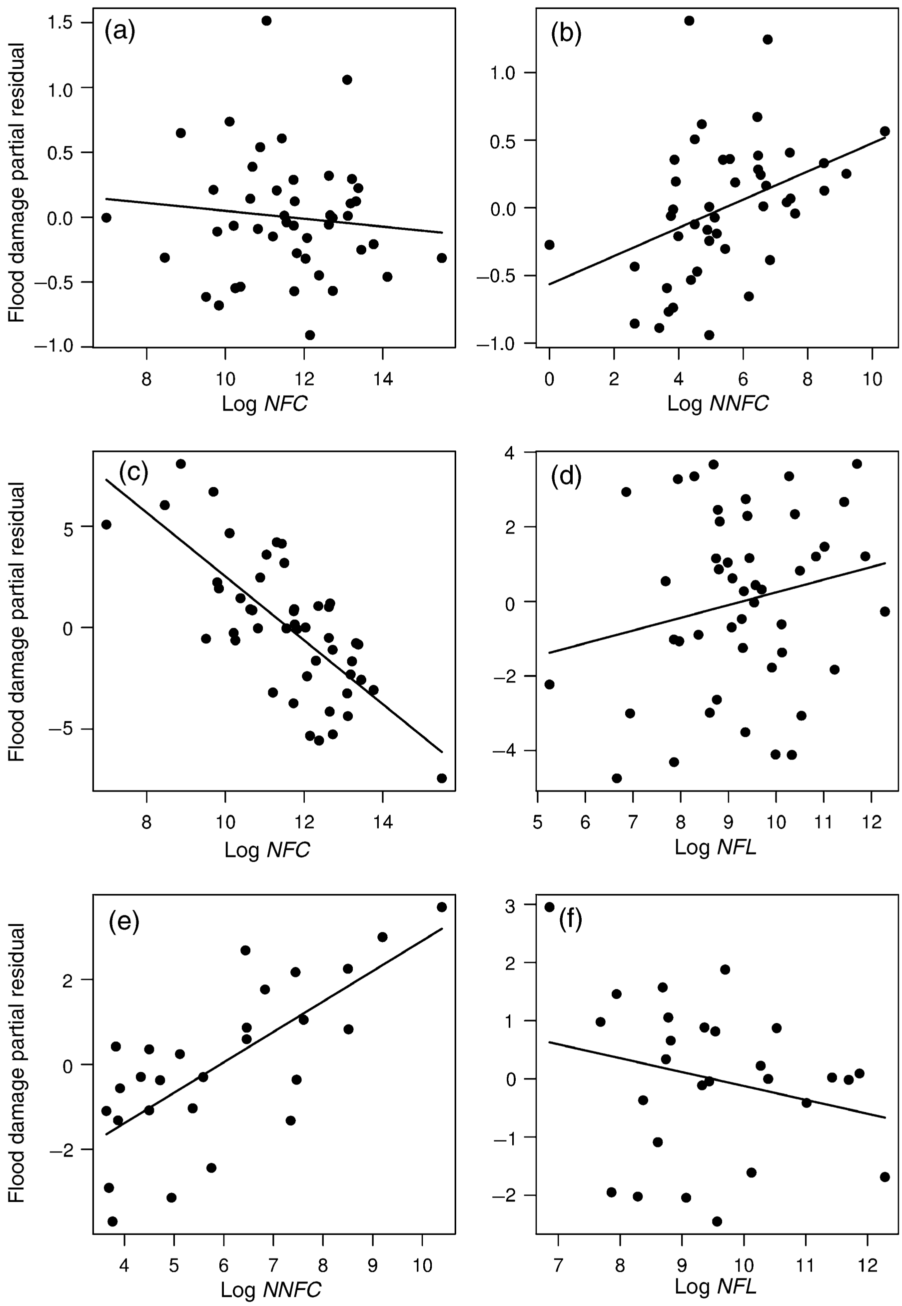

Fig. 6 Partial residual plots of the flood severity response variables [(a–b) people killed, (c–d) people displaced and (e–f) infrastructure damage] expressed as a function of forest cover/loss metrics: log natural forest cover (*NFC*, km^2), log nonnatural forest cover (*NNFC*, km^2) and natural forest loss between 1990 and 2000 (*NFL*, km^2) derived from the most parsimonious models given in Table 3.

(Table 3). *NFC* and *NNFC* together only accounted for an additional 1.3% of the deviance in the number of people killed beyond the control variables (Table 3), with the sign of the relationships agreeing with those found for flood frequency and duration (Fig. 6a and b). However, the range of model-averaged predicted percentage increase in the number of people killed with a 10% decrease in *NFC* overlapped zero (−0.8% to 0.9%), indicating little evidence for an important effect at this level of additional deforestation. *NFC* and *NNFC* accounted for only 0.8% extra deviance for the number of people displaced (Table 3; Fig. 6c and d), with the model-averaged predicted percentage increase in people displaced ranging from 0.8% to 6.2% following a

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10% decrease in *NFC*. *NFL* and *NNFC* together accounted for nearly 5% additional deviance in the damage response (Table 3; Fig. 6d and e), but the model-averaged prediction indicated little effect of decreasing *NFC* given this term's lack of explanatory support in the models considered (Table 3).

Discussion

Our results provide the first globally comprehensive and empirical link between deforestation and flood frequency, and support the conclusions drawn from previously localized studies, such as those from the Amazon (Sternberg, 1987), China (Lang, 2002) and Tanzania (Sandström, 1995) which sustain this notion. However, not all local studies have pointed to deforestation as a key driver of floods (FAO & CIFOR, 2005; Calder & Aylward, 2006), implying that broad-scale patterns are not always mimicked at finer scales, and vice versa (Bruijnzeel, 2004). Indeed, flood-risk estimation is an inherently uncertain business, and even rainfall data can be surprisingly uninformative about flood frequency at the catchment scale (Reed, 2002). The mechanisms driving the increase in water flows following vegetation removal are complex and still controversial. The majority of the increased discharge is normally observed as baseflow, provided the intake capacity of the soil's surface is not impaired too much during the removal process (Bruijnzeel, 1990).

The complex interplay of factors such as rainfall variation, elevation and distance to the coast, catchment steepness, soil depth, the degree of disturbance to undergrowth and soil, and soil fertility (reviewed in Bruijnzeel, 2004) and their relative importance vary widely among sites, so typically a suite of process studies are required to understand the effects of vegetation removal on flooding frequency and intensity. Moreover, the strong relationship between evapotranspiration rates and rainfall (Zhang *et al*., 2001) will contribute further site-specific complexity to estimates of flooding risk. Yet despite the suite of complex and confounding relationships between these potential drivers of flood risk, our models explained over 65% of the deviance (analogous to a least-squares R^2 value) in flood frequency, and we found important contributions of all control variables (area, slope, rainfall and degraded area). This is particularly notable when one considers the broad spatial unit of investigation (country) and the diversity of catchment types within each country. This apparent explanatory power thus suggests that average values, examined over the global scale, provide evidence that the variables considered were valid and relevant predictors of flood risk.

Our analysis revealed a nontrivial correlation between natural forest cover/forest loss and flood frequency at a global spatial scale, as opposed to temporal predictions at the catchment scale. Of course, our results assume that all major variables accounting for variation in flood frequency values among countries were considered (i.e. the control variables included). Our models showed model-averaged predictions of increased flood frequency ranging from 4% to 28% with just a 10% loss in natural forest cover. This reinforces the conclusion that global-scale empirical studies such as ours are critical for resolving the debate surrounding the general role of forests in influencing flood frequency, local factors notwithstanding. The result also stresses the need for local governments to think at broad spatial scales when planning flood mitigation policies. However, some caution should be exercised when interpreting the predicted ranges of expected increases in flood risk. The forest cover data are derived from a variety of sources and spatial scales, suggesting that sometimes important errors in land cover assessments may arise (Matthews, 2001). However, despite the potential errors and the magnitude of the modelled effects, and the assumption that all major drivers of flood risk were considered, the relationships we found are indicative of the role of natural forest cover in mitigating flood risk.

The relationships between the various indices of flood severity and forest cover were generally weaker; however, there were still some detectable correlations. The full models including control variables accounted for 42–65% of the deviance in the responses (Table 3), suggesting again that modelling flood characteristics at the global scale using country-scale landscape features is tractable. Of the responses considered, flood duration had the strongest correlation with natural forest cover. As for the other severity response variables (people killed, people displaced and damage), they are prone to many uncertainties, not least of which is each country's ability to prepare for floods and minimize damage to property and human casualties. However, the weaker relationships do not necessarily imply that forest cover has little influence on flood severity. For instance, our analyses did not take into account small floods, nor did they consider potential changes in hydrological regimes caused by global climate change (Panagoulia & Dimou, 1997; Cameron *et al*., 2000; Schreider *et al*., 2000). Modified weather patterns (Meehl *et al*., 2000) resulting from global climate change (Kerr, 2004; Murphy *et al*., 2004) will also act to increase the complexity of interactions between land cover and flooding frequency and severity (Bruijnzeel, 2004). Moreover, our models could not incorporate the increasing trend for people in land-restricted areas to develop and settle in flood-prone areas around the world that were avoided previously (FAO & CIFOR, 2005). Nonetheless, our empirical results indicate that halting deforestation or reducing the rate of natural forest loss should be beneficial in alleviating the incidence and severity of floods that ultimately cause undesirable societal disruption and damage to human life and property.

The empirical links between deforestation and flood risk and severity demonstrated here reinforce the notion that politicians and landscape planners must implement tangible actions, such as protection of existing natural forests and reforestation activities (Carroll *et al*., 2004). The latter should ideally be done using native trees, because exotic tree species generally have lower conservation value for native biodiversity (Sodhi *et al*., 2005) and may not always affect water yields in the same manner as native vegetation (Bruijnzeel, 2004). Indeed, our models demonstrated a positive relationship between nonnatural forest area (*NNFC*) and all but one (people displaced) of the flood response variables considered, suggesting that in some circumstances, nonnative vegetation may do more harm than good in mitigating flood severity. It should also be noted that reforestation may not always bring about only positive effects – for example, extensive reforestation in monsoonal climates can lead to severely diminished streamflows during the dry season that may engender a suite of other problems, potentially offsetting any advantages gained by flood reduction (Scott *et al*., 2005).

Demonstrations of the relationships between the conservation of nature and benefits to human welfare (Lilley *et al*., 1997) provide the relevant perspective that is often necessary to convince people of the value of natural systems and encourage policy makers to include social and economic planning with technological approaches to water management (Calder, 1999). This is particularly necessary for the developing world, where funds to cope with disasters are extremely limited, and flood-related catastrophes will suppress economic growth and prosperity (Wang, 2004). The concept of conservation of natural habitats needs to extend beyond the notion of saving imperiled biotas to include the welfare of disadvantaged humans around the world.

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Appendix A

Table A1 Base data for each country's 'control' variables, including area, rainfall, slope, population size (1999), soil humidity class and degraded area

Country	Continent	Area (km^2)	Average annual rainfall (mm)	Slope (°)	Population (1999)	Soil humidity	Degraded area (km^2)
Angola	Africa	1 246 700	1090	1.073	12 479 000	Subhumid	127 917
Botswana	Africa	566 730	393	0.214	1 597 000	Semiarid	117 363
Cameroon	Africa	465 400	1591	0.925	14 693 000	Perhumid	96 766
CAF	Africa	622 970	1409	0.366	3 550 000	Subhumid	79 671
Chad	Africa	1 259 200	130	0.531	7 458 000	Semiarid	17 464
Congo	Africa	341 500	1672	0.321	2 864 000	Perhumid	12 372
COD	Africa	2 267 050	1643	0.701	50 335 000	Perhumid	239 275
Ethiopia	Africa	1 104 300	653	2.499	61 095 000	Subhumid	177 302
Ghana	Africa	227 540	1212	0.512	19 678 000	Subhumid	53 573
Kenya	Africa	569 150	503	0.994	29 549 000	Semiarid	116 558
Malawi	Africa	94 090	1010	1.484	10 640 000	Subhumid	34 101
Mozambique	Africa	784 090	1026	0.768	19 286 000	Subhumid	297 811
Nigeria	Africa	910 770	1135	0.599	108 945 000	Subhumid	177 079
RSA	Africa	1 217 580	479	2.021	39 900 000	Semiarid	466 227
Senegal	Africa	192 520	641	0.270	9 240 000	Subhumid	34 846
Sudan	Africa	2 376 000	275	0.529	28 883 000	Semiarid	128 049
Tanzania	Africa	883 590	966	1.108	32 793 000	Subhumid	364 497
Togo	Africa	54 390	1163	0.401	4 512 000	Subhumid	6628
Uganda	Africa	199 640	1213	1.250	21 143 000	Perhumid	85 410
Zambia	Africa	743 390	1008	0.777	8 976 000	Subhumid	252 949
Zimbabwe	Africa	386 850	666	1.456	11 529 000	Subhumid	211 590
Bangladesh	Asia	130 170	2116	1.469	126 947 000	Subhumid	102 490
Cambodia	Asia	176 520	1705	0.939	10 945 000	Subhumid	97 955
China	Asia	9 327 430	448	3.007	1 274 106 000	Perhumid	2 700 413
India	Asia	2 973 190	976	2.025	998 056 000	Subhumid	2 118 834
Indonesia	Asia	1 811 570	2683	1.708	209 255 000	Perhumid	553 429
Laos	Asia	230 800	1701	4.681	5 297 000	Perhumid	35 144
Malaysia	Asia	328 550	2815	2.026	21 830 000	Perhumid	101 184
Myanmar	Asia	657 550	1719	3.848	45 059 000	Perhumid	143 036
Philippines	Asia	298 170	2506	2.441	74 454 000	Perhumid	254 685
PNG	Asia	452 390	2904	3.062	4 702 000	Perhumid	33 480
Sri Lanka	Asia	64 630	1650	0.988	18 639 000	Subhumid	54 360
Thailand	Asia	510 890	1325	1.677	60 856 000	Subhumid	302 118
Vietnam	Asia	325 500	1717	2.937	78 705 000	Perhumid	182 251
Argentina	C/SA	2 736 690	465	0.845	36 577 000	Semiarid	881 203
Bolivia	C/SA	1 084 380	1163	1.469	8 142 000	Semiarid	94 468
Brazil	C/SA	8 456 510	1722	0.502	167 988 000	Perhumid	2 151 198
Chile	C/SA	748 810	768	4.958	15 019 000	Semiarid	64 742
Colombia	C/SA	1 038 710	2684	1.865	41 564 000	Perhumid	198 708
Costa Rica	C/SA	51 060	2962	2.021	3 933 000	Perhumid	13 746
Cuba	C/SA	109 820	1345	0.623	11 160 000	Subhumid	48 607
DOM	C/SA	48 380	1366	2.053	8 364 000	Perhumid	9870
Ecuador	C/SA	276 840	1943	2.710	12 411 000	Perhumid	61 260

(*contd.*)

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Table A1. (*Contd.*)

Country	Continent	Area (km^2)	Average annual rainfall (mm)	Slope (°)	Population (1999)	Soil humidity	Degraded area (km^2)
El Salvador	C/SA	20 720	1829	4.571	6 154 000	Subhumid	13 555
Guatemala	C/SA	108 430	1771	3.155	11 090 000	Perhumid	36 972
Guyana	C/SA	214 980	1971	0.456	855 000	Perhumid	18 731
Honduras	C/SA	111 890	1619	3.419	6 316 000	Perhumid	40 376
Jamaica	C/SA	10 830	1853.5	1.663	2 560 000	Perhumid	1285
Mexico	C/SA	1 908 690	616	2.613	97 365 000	Semiarid	326 063
Nicaragua	C/SA	121 400	2237	1.439	4 938 000	Perhumid	44 783
Panama	C/SA	74 430	2614.5	1.387	2 812 000	Perhumid	24 930
Paraguay	C/SA	397 300	1048	0.355	5 358 000	Perhumid	53 676
Peru	C/SA	1 280 000	1717	2.541	25 230 000	Perhumid	87 910
TRI	C/SA	5130	2055	0.469	1 289 000	Perhumid	1422
Uruguay	C/SA	174 810	1227	0.461	3 313 000	Perhumid	103 120
Venezuela	C/SA	882 060	1740	1.293	23 706 000	Perhumid	93 475

CAF, Central African Republic; COD, Democratic Republic of Congo; RSA, Republic of South Africa; PNG, Papua New Guinea; C/SA, Central/South America; DOM, Dominican Republic; TRI, Trinidad & Tobago.

Table A2 Forest cover, flood frequency and flood severity data for each country

Country	Continent	No. floods	Natural forest cover 2000 (km^2)	Natural forest cover 1990 (km^2)	Natural forest loss (km^2)	Total average damage ($US)	PPP	Average no. people killed	Average no. people displaced
Angola	Africa	1	696 150	710 073	13 923	10 000 000	2.58	31	70 000
Botswana	Africa	1	124 260	135 443	1118		2.55	20	2000
Cameroon	Africa	2	237 780	259 180	2140		3.45	9	1000
CAF	Africa	1	229 030				4.00	200	
Chad	Africa	2	126 780	134 387	761		4.44	2	260 000
Congo	Africa	3	219 770	221 968	220		1.36		6000
COD	Africa	2	1 351 100	1 405 144	5404		6.40	16	
Ethiopia	Africa	18	43 770	47 709	394	28 800 000	8.00	921	826 721
Ghana	Africa	5	62 590	73 856	1127	62 500 000	7.64	11 320	1 000 000
Kenya	Africa	3	168 650	177 083	843		2.86	20	88 500
Malawi	Africa	4	24 500	30 870	637	96 000 000	3.53	673	303 000
Mozambique	Africa	8	305 510	311 620	611	169 600 000	5.00	247	1 092 000
Nigeria	Africa	13	128 240	164 147	3591		2.68	313	992 333
RSA	Africa	13	73 630	75 839	221	85 150 000	3.92	258	18 005
Senegal	Africa	1	59 420	64 768	535		3.26		
Sudan	Africa	9	609 860	701 339	9148	180 810 000	4.67	215	1 047 825
Tanzania	Africa	11	386 760			20 790 000	2.06	5328	5 692 156
Togo	Africa	2	4720	6514	179	16 000 000	5.38	4	165 000
Uganda	Africa	3	41 470	49 764	829	3 000 000	5.59	69	60 000
Zambia	Africa	1	311 710	386 520	7481		0.06		12 000
Zimbabwe	Africa	2	188 990	219 228	3024			1	500
Bangladesh	Asia	48	7090	7657	57	4 631 698 286	4.72	3813	50 049 706
Cambodia	Asia	8	92 450	97 997	555	221 000 000	6.58	688	1 966 957
China	Asia	99	1 183 970	1 112 932	−7104		4.69	12 931	95 080 367
India	Asia	67	315 350	435 183	11 983	8 392 033 765	5.61	11 174	99 719 752
Indonesia	Asia	41	951 160	1 093 834	14 267	4 101 256 091	4.34	1112	2 236 140
Laos	Asia	4	125 070	131 324	625		5.29	62	81 600
Malaysia	Asia	7	175 430	199 990	2456	174 867 000	2.40	225	54 600
Myanmar	Asia	7	335 980	386 377	5040			525	324 303

(*contd.*)

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Table A2. (*Contd.*)

Country	Continent	No. floods	Natural forest cover 2000 (km^2)	Natural forest cover 1990 (km^2)	Natural forest loss (km^2)	Total average damage ($US)	PPP	Average no. people killed	Average no. people displaced
Philippines	Asia	27	50 360	60 936	1058		4.32	311	391 500
PNG	Asia	4	305 110	317 314	1220	23 991 493	4.29	79	358 891
Sri Lanka	Asia	19	16 250	19 825	358	17 594 000	4.16	180	2 447 571
Thailand	Asia	15	98 420	126 962	2854	2 239 071 429	3.45	915	10 333 023
Vietnam	Asia	25	81 080	83 512	243	1 422 329 545	5.32	1726	7 110 280
Argentina	C/SA	7	337 220	374 314	3709	2 800 000 000	2.51	30	33 133
Bolivia	C/SA	4	530 220	546 127	1591	270 000 000	2.66	80	70 250
Brazil	C/SA	19	5 389 240	5 604 810	21 557	1 425 000 000	2.63	539	354 406
Chile	C/SA	6	135 190	146 005	1082	187 000 000	2.22	152	165 049
Colombia	C/SA	8	494 600	514 384	1978		3.38	216	71 185
Costa Rica	C/SA	4	17 900	20 406	251		2.11	36	40 000
Cuba	C/SA	2	18 670	18 483	−19			4	13 300
DOM	C/SA	1	13 460	13 864	40			2	200
Ecuador	C/SA	6	103 900	117 407	1351	207 333 333	2.25	99	102 900
El Salvador	C/SA	5	1070	1723	65		2.28	23	25 667
Guatemala	C/SA	4	27 170	33 147	598		2.29	61	7200
Guyana	C/SA	2	168 670			200 000			
Honduras	C/SA	8	53 350	59 219	587	28 266 667	2.70	484	102 400
Jamaica	C/SA	2	3170			50 000 000	1.43	16	321 600
Mexico	C/SA	13	549 380	609 812	6043	201 500 000	1.49	969	573 658
Nicaragua	C/SA	1	32 320	42 662	1034		3.42	5	106 000
Panama	C/SA	4	28 360	33 465	510	20 000 000	1.53	4	5000
Paraguay	C/SA	5	233 450	245 123	1167		3.91		188 406
Peru	C/SA	11	645 750	678 038	3229	231 000 000	2.41	767	986 229
TRI	C/SA	1	2440				1.36	5	
Uruguay	C/SA	1	6700	6700	0		1.78		
Venezuela	C/SA	4	486 430	510 752	2432		1.28	26 671	41 333

CAF, Central African Republic; COD, Democratic Republic of Congo; RSA, Republic of South Africa; PNG, Papua New Guinea; C/SA, Central/South America; DOM, Dominican Republic; TRI, Trinidad & Tobago.

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