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Research

Deforestation and economic growth trends on oceanic islands highlight the need for meso-scale analysis and improved mid-range theory in conservation

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ABSTRACT. Forests both support biodiversity and provide a wide range of benefits to people at multiple scales. Global and national remote sensing analyses of drivers of forest change generally focus on broad-scale influences on area (composition), ignoring arrangement (configuration). To explore meso-scale relationships, we compared forest composition and configuration to six indicators of economic growth over 23 years (1992–2015) of satellite data for 23 island nations. Based on global analyses, we expected to find clear relationships between economic growth and forest cover. Eleven islands lost 1 to 50% of forest cover, eight gained 1 to 28%, and four remained steady. Surprisingly, we found no clear relationship between economic growth trends and forest-cover change trajectories. These results differ from those of global land-cover change analyses and suggest that conservation-oriented policy and management approaches developed at both national and local scales are ignoring key meso-scale processes.

Key Words: *deforestation; economic indicators; land-cover change; land-use change; landscape composition; landscape configuration; remote sensing*

INTRODUCTION

Forests support many species and provide a wide range of economically and culturally valuable goods and services. Their role in carbon sequestration and storage, for instance, is globally significant (Molotoks et al. 2018). Global analyses suggest that overall, there is a trend toward shrinking and degradation of forests (Achard et al. 2002, Hansen et al. 2013, Curtis et al. 2018, Song et al. 2018) and increasing forest fragmentation (Kasperson et al. 1995, Turner et al. 2001*a,* Nagendra et al. 2003, Fearnside 2005). However, reforestation (the return of deforested locations to forest, whether by planting or regeneration) has occurred extensively in some areas (e.g., North America), and time series of forest cover change show high variation and uncertainty in deforestation and reforestation rates (Angelsen 2001).

Deforestation is driven by a range of proximate and ultimate causes that depend on both geographical and historical contexts (Geist and Lambin 2002). Curtis et al. (2018) attributed 27% of permanent global forest loss to commodity production, with additional losses primarily due to forestry (26%), shifting agriculture (24%), and wildfire (23%). Their analysis suggests a clear divide between developed and developing nations ("the global south"), with most commodity-driven deforestation and shifting agriculture occurring in developing nations in Latin America and Asia. However, the many different, interacting variables that drive forest loss make it challenging to understand, govern, and manage (Angelsen 2001, Geist and Lambin 2002). Broad-brush analyses gloss over complexities and feedbacks at a variety of different spatial and governance scales. Global analyses have also focused heavily on measures of landscape composition (amount of habitat or land cover) and have largely ignored changes in landscape configuration (arrangement of habitat or land cover, which, in a land-cover context, refers to the relative position and dispersion of different land-cover types). The importance of habitat configuration for deforestation has been widely explored in individual cases at finer spatial scales (e.g., Laurance et al. 2002, Perz et al. 2008, Lorena and Lambin 2009, Cumming et al. 2012), but is poorly connected to the understanding of global trends.

Several hypotheses that seek to explain changes in forests relative to wealth have been proposed. First, forest transition theory proposes that a decline in forest cover during industrialization is followed by an increase in forest cover, possibly with a substantial lag, after sufficient wealth has been accumulated (Mather 1992, 2001). Second, researchers have attempted to apply the environmental Kuznets curve (EKC; Kuznets 1955) to forests and have used it to argue that forest loss will follow a U-shaped curve in relation to economic growth. These theories propose a similar trend but different underlying mechanisms. Forest transition theory invokes a mechanism of agricultural adjustment to land quality, relying on the argument that over time, agricultural production will become focused in smaller areas of better land, with poorer land being abandoned and experiencing forest regeneration (Mather and Needle 1998). By contrast, the EKC proposes that as societies become wealthier, they invest more heavily in environmental protection and improvement, again leading to expansion of forests. Substantial concerns have, however, been raised about both of these theories. Perz (2007) has argued that forest transition theory is limited in its concept of what forests are, its treatment of forest dynamics, its explanation for forest transitions, and its generalizability. Similarly, bar a few exceptions mainly relating to pollution, the EKC has been shown to be unsuited to a wide range of environmental problems (Dasgupta et al. 2002, Stern 2004), and an extensive metareview across 76 developing nations found little support for its application to forests (Koop and Tole 1999). In general, while no one denies that changes in forest cover are nonlinear and complex, there appears to be little consensus over singular mechanistic explanations for either deforestation or reforestation (Angelsen and Kaimowitz 1999, Chowdhury and Moran 2012) and a strong need for greater awareness of context dependence in forest-cover dynamics (Perz 2007).

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Context dependence is particularly evident in the choice of scale of land-cover change studies. Local analyses are often highly detailed, achieving specific explanations but lacking in general applicability. By contrast, global analyses extract more predictable and more consistent broad-scale patterns but often fail to explain their underlying mechanisms (Levin 1992). We propose that there is a need for mid-range analyses of both pattern and process in forest-cover trends, meeting recent calls for the development of more strongly contextualized ("mid-range") theory (Meyfroidt et al. 2018) that connects fine-scale detail and broad-scale pattern.

We thus addressed the gap between global and local analyses of deforestation by exploring the potential of oceanic islands as mesocosms for understanding global deforestation patterns. We use "meso-scale" to refer to a scale of analysis that falls between global or continental analyses and local analyses, where "local" refers to the area that is regularly accessed by a single community. The island areas that we describe as meso-scale range from 4400 ha to 1.9×10^8 ha. Because of the general lack of comparative, meso-scale analyses and mid-range theories in the published literature, we could not use existing theories to select case studies a priori. Our broader goal for this analysis was thus to use pattern analysis to explore trends within a mid-level, mid-scale set of cases that, in turn, can contribute to the development of contextualized, mid-range theory through the creation of typologies of forest change that reflect the range of causes that can produce a given pattern.

Most oceanic island nations (and inhabited oceanic islands governed by mainland countries) are small (< 10,000 km²) and topographically, ecologically, and socially heterogeneous landscapes. Their clear boundaries make estimations of imports and exports simple, and their size means that resource limitation is obvious earlier than in larger systems, providing insights into the landscape-level consequences of global phenomena such as migration and overpopulation. Islands have been proposed as ideal proxies for the study of landscape fragmentation at a global scale (Lugo 2002) and have informed the understanding social-ecological resilience in general (MacArthur and Wilson 1963, Lugo 2002, Warren et al. 2015, Patiño et al. 2017). However, there have been few quantitative, comparative studies of land-cover change across islands.

We looked at changes in both landscape composition and landscape configuration across 23 different islands. To keep this first meso-scale analysis comprehensible, we limited our analyses to six key economic drivers that might explain the relationship between the level of economic development of a country and changes in forest cover. Based on the results of global analyses (e.g., Curtis et al. 2018), we expected to find (1) a clear distinction in deforestation rates and the pattern of deforestation between developed and less developed nations, with national economies strongly correlated with deforestation rates; and (2) clear connections between economic indicators and the pattern of landscape change because forest clearing for agriculture and commodity production (e.g., pulp and paper) typically follows a different pattern from forest clearing for forestry or by wildfire (Henders et al. 2015).

METHODS

Data description

Multisensor Earth observation satellite data were used to quantify changes in global forest cover from 1992–2015 at a spatial resolution of 300 m for 23 island nations: Andaman and Nicobar, Antigua and Barbuda, Bahamas, Cuba, Cyprus, Dominican Republic, Fiji, Haiti, Indonesia, Jamaica, Japan, Martinique, Mauritius, Philippines, Papua New Guinea (PNG), Puerto Rico, Singapore, Solomon, Sri Lanka, Taiwan, Tasmania, Vanuatu, and Zanzibar. These islands constitute the largest sample size for which we could find reliable, consistent data across a sufficient range of variables. They span a wide range of social, ecological, and economic conditions, including both temperate and tropical ecosystems, and a wide range of different policies and governance. They thus offer good proxies for the study of landscape fragmentation at a global scale.

We used global land-cover data generated under the Climate Change Initiative (Santoro et al. 2017). Data were derived from multisensor time series of Advanced Very High Resolution Radiometer (AVHRR) 7-day composite images, Medium Resolution Imaging Spectrometer (MERIS) full-resolution 7-day composites, and (for 2014 and 2015) Project for On-board Autonomy-Végétation (PROBA-V) 7-day composites. The annual land-cover maps were derived from unique baseline land-cover maps generated from the MERIS full-resolution and reduced-resolution archive from 2003 to 2012 (Table 1) and grouped into six broad land categories: cropland, forest, grassland, wetland, settlement, and other land (Table S.1 in Appendix 1). In addition, land cover was measured at 1 km from the AVHRR time series for the period 1992 to 1999, SPOT-VGT time series for the period 1999 and 2013, and PROBA-V data for years 2013, 2014, and 2015. When MERIS full-resolution or PROBA-V time series were available, changes detected at 1 km were rescaled at 300 m. The last step consisted of back- and up-dating the 10-year baseline land-cover map to produce 24 annual land-cover maps from 1992 to 2015.

Measurement of landscape fragmentation

We measured land-cover change over time in the area (composition) and arrangement (configuration) of forest habitats, using FRAGSTATS (McGarigal et al. 2012) to quantify metrics at class and landscape levels. Metrics included measures of contrast, shape complexity, aggregation, and isolation (Table 2). Formal definitions are available in Turner et al. (2001*b*) and McGarigal et al. (2012).

To correct for differences in the magnitudes of different metrics, we standardized the landscape metrics for each of the 30 islands by subtracting the mean and dividing by the standard deviation for that metric. Using the standardized values of each metric (Table 2), we performed three sets of analyses to explore changes in forest composition and configuration within and between islands. The analyses included: (1) quantification and between-island comparisons of overall change in forest cover between 1992 and 2015; (2) comparison of trajectories of forest-cover change among islands; and (3) assessment of the similarities and dissimilarities among islands in relation to gross domestic product (GDP).

Table 1. Data sources used to generate the global land cover maps from 1992–2015, following the methods of Lamarche et al. (2017).

Output map	Reference period	Sensor
Baseline 10-yr global land-cover map	2003–2012	• MERIS SR composites
Global annual land-cover maps	1992–1999	• Baseline 10-yr global land-cover map • AVHRR global SR composites for back-dating the baseline
Global annual land-cover maps	1999–2013	• Baseline 10-yr global land-cover map • SPOT-VGT global SR composites for up- and back-dating the baseline for the reference period • MERIS FR global SR composites between 2003 and 2012 to delineate the maps at 300 m • PROBA-V global SR composites at 300 m for 2013 to delineate the maps
Global annual land-cover maps	2014–2015	• Baseline 10-yr global land-cover map • PROBA-V global SE composites at 1 km between 2014 and 2015 for updating the baseline • PROBA-V time series at 300 m for years 2014 and 2015 to delineate the maps to 300 m

Table 2. Description and interpretation of landscape composition and configuration characteristics quantified at class and landscape level.

Metric	Acronym	Ecological interpretation	Units	Calculation method
Edge density	ED	Measure of edge, corrected for area; forest edges can influence many ecologically relevant processes such as the spread of fire, dispersal, and predation (Cadenasso et al. 1997, Cadenasso and Pickett 2000)	m/ha	Sum of the lengths (m) of all edge segments involving the corresponding class type, divided by the total landscape area (ha)
Mean Euclidean nearest-neighbor distance	ENN_MN	Measure of isolation, which is important for dispersal and patch recolonization	m	Shortest straight-line distance (m) between a focal patch and its nearest neighbor of the same class
Percentage of landscape	PLAND	Measure of composition (relative cover), which affects resource availability, competition, and alpha (local) diversity	%	Proportional abundance of each patch type in the landscape ($0 < \text{PLAND} \leq 100$)
Mean fractal dimension index	FRAC_MN	Measure of shape complexity, which influences dispersal, predation, and edge effects	None	Shape index based on perimeter:area relationships in which the perimeter and area are log transformed
Clumpy index	CLUMPY	Measure of aggregation; CLUMPY is the only aggregation index that is independent of landscape composition (measured by PLAND as relative forest cover) and is unaffected by the shape of the landscape; it captures the degree to which habitats are aggregated or dispersed, which has consequences for dispersal, predation, reproduction, and metapopulation dynamics	%	Proportional deviation of the proportion of like adjacencies involving the corresponding class from that expected under a spatially random distribution ($-1 \leq \text{CLUMPY} \leq 1$)
Aggregation index	AI	Level of aggregation of spatial patterns; like CLUMPY, aggregation has consequences for metapopulation and ecological community dynamics	%	Number of like adjacencies involving the corresponding class, divided by the maximum possible number of like adjacencies involving the corresponding class

The first set of analyses used the PLAND metric (Table 2) to quantify net loss or gain in forest cover between the years 1992 and 2015 using the standard percentage change relation. A range of terms quantified is given in Table 3. We used percentage change because the islands exhibited considerable variance in area, and many metrics of forest composition and configuration are scale dependent. Importantly, net percentage change does not reflect variance in the rate of land-cover change or other properties of the change trajectory. Our second set of analyses thus considered forest dynamics using time series data that require the pattern and random components to be identified to obtain uncorrelated data points in time. We determined that values were uncorrelated at a lag of 5 years using the autocorrelation function “acf” in the “Stat” package of R (R Core Team). For this analysis, we thus divided the total period of 24 years into four subperiods (minimum of 5 years): 1992–1997, 1997–2002, 2002–2007, and 2007–2015.

We selected key economic indicators for linking economic growth and environmental sustainability based on standard economic growth theories that suggest connections between wealth, labor, capital, environmental stocks, and human well-being (e.g., Schumpeter 1983, Solow 1956, Swan 1956, Chenery et al. 1986, Lin and Rosenblatt 2012). We focused on five variables that have been strongly implicated as relevant to development trajectories by Cumming and von Cramon-Taubadel (2018): population growth, GDP (GDP per capita [constant local currency unit]), forest rents, the Human Development Index (HDI), and the value added by agriculture (%GDP). These data were obtained from the World Bank Open Data Set (https://data.worldbank.org/).

Table 3. Definitions of terms used to refer to changes in forest cover in the analyses and results. See Table 2 for definition of variable acronyms.

Term	Definition and determination
Prior forest cover	Forest cover (total area, as measured through PLAND) of an island in 1992
Net percentage change in forest cover	First, the net change in forest cover between 1992 and 2015 was calculated for each individual island as the sum of all changes in PLAND over 1992–2015 (including reductions due to deforestation and disasters and increases due to reforestation and forest expansion); then, we divided the net change in forest cover by prior forest cover and multiplied this fraction by 100 to give the net percent change in forest cover
Net forest cover gain	A positive net change in forest cover
Net forest cover loss	A negative net change in forest cover
Mean change in net forest cover	The sum of net percentage change in forest cover of all 23 islands divided by 23 gives a mean change in net forest cover across all islands; the standard deviation of this value measures variability in net percentage change in forest cover across all islands

National economies are essentially bimodal, with less financially wealthy nations (those with HDI = 4) and more financially wealthy nations (HDI = 1) tending toward two different social-ecological attractors (Cumming and von Cramon-Taubadel 2018). HDI = 4 nations depend proportionally more heavily and more directly on natural resources and agriculture and experience lower GDP with increased population growth. Simplistically, one might thus expect that higher population growth rate in HDI = 4 nations leads to greater levels of deforestation, whereas in HDI = 1 countries, higher population growth rate leads to a higher GDP (as a consequence, for example, of technological and service industries) and, potentially, a reduced direct reliance on ecosystems and lower deforestation rates. However, a series of complex feedbacks means that the relationship between different indicator variables and deforestation itself is not necessarily consistent.

We tested for correlations between forest-cover change using composition and configuration matrices and matching economic data. Our third set of analyses used Mantel tests with the nonparametric Spearman's method in the "vegan" package in R (Dixon 2003). The Mantel test was performed using data points (for both ecological matrices [composition and configuration] and economic growth drivers) that were uncorrelated in time, i.e., for the four subperiods only. The Mantel test takes dissimilarity matrices as input arguments; these matrices were calculated using the "vegdist" function in the vegan package with default arguments. For the Mantel test using population growth GDP per capita data, 21 islands were included. For forest rents, data from 20 islands were available, and for agriculture value (% GDP) and HDI drivers, data from 19 islands were available.

In our fourth set of analyses, we first grouped islands by forest-cover change (both composition and configuration) and then tested for a relationship between forest-cover change group membership and GDP. To check for the possible statistical bias that might emerge if smaller islands have weaker economies, we also tested for a correlation between GDP and island area using standardized landscape metrics and proportions. Grouping used an unsupervised, two-fold, hierarchical clustering approach to calculate dissimilarity metrics for each island using a time series clustering approach (the "diss" function in the "TSclust" library in R; Montero and Vilar 2014). TSclust corrects for the time-dependent component, so we used data from the entire study period (not subperiods) to create groups. Next, for each metric, we performed hierarchical clustering using Ward's minimum variance method to assign cluster membership to each island based on an optimal value of the objective function (error sum of squares). The option "ward.D2" was used because it minimizes the Ward's minimum criterion more efficiently than does the "ward.D" method (Murtagh and Legendre 2014). The dendogram clustering was based on the pairwise dissimilarities and the number of groups for cutting the tree (k = 4) and the height arguments of the "fviz_dend" function of the package "factoextra" in R (Kassambara and Mundt 2017). Finally, to check for an effect of absolute island area on variables of interest, we compared island area, population growth and change, and total forest area (in ha) and change in forest area (using the data in Table 4). Summary data for the economic variables, forest rents (% GDP), agriculture (and forestry and fishing) value added (% GDP), and HDI with forest cover for each island are given in Appendix 1 (Table S.2).

RESULTS

The mean change in net forest cover across all islands was −3.14% ± 15%. The range of net forest cover loss was approximately −50 to −1% by area, and the range of net forest cover gain was approximately 1 to 28% (Fig. 1), determined from percentage net forest change (Fig. A.1 in Appendix 1). Eleven islands experienced net forest cover loss (i.e., < −1.0%), eight experienced net forest cover gain (i.e., > +1.0%), and net forest cover for four islands remained steady (between −0.22 and 0.90%), indicating the complexities of deforestation and reforestation dynamics occurring within the study data (formal definitions of mean change in forest cover and related terminology are given in Table 3).

Analysis of change trajectories across the four subperiods revealed similarly complex patterns in landscape composition and configuration over time (Fig. 2). For illustration, we have used the change trajectories of Japan, Singapore, and PNG; these islands were grouped together by forest-cover metrics (Fig. 3) and other configuration metrics. For these islands, even though the net change in forest cover remained low (−3.5 to +3.5%), the landscape configuration changed significantly, with potentially important implications for ecological processes that depend on connectivity. For example, net forest cover change for Japan between 1992 and 2015 was low (+0.26%), and time-series analysis showed that forest patch complexity and edge length remained steady (largest increase approximately 0.20% in shape and

Table 4. Total area, population size, change in population, total forested area, and change in forested area on each island examined to determine if pressure from the population influences forested area.

Island		Total population			Forest area (CA; ha)			Maximum CA change		
Name	Area (ha)	1992	2015	Change (%)	CA (1992)	CA (2015)	Change (%)	CA	Year	Change (%)
Anadaman and Nicobar	825,000	No data	400,112	No data	649,656.27	646,692.39	−0.46	656,227.9	1996	1.01
Antigua and Barbuda	44,000	64,471	93,566	45.13	18,512.32	18,093.25	−2.26	19,860.66	2009–2013	7.28
Bahamas	1,387,800	266,029	374,206	40.66	525,287.20	565,646.30	7.68	567,134.3	2010	7.97
Cuba	10,988,400	10,736,387	11,324,781	5.48	4,383,321.32	4,566,774.33	4.19	4,570,880.08	2010	4.28
Cyprus	925,100	800,611	1,160,985	45.01	180,428.36	190,419.43	5.54	190,419.43	2014–2015	5.54
Dominican Republic	4,844,200	7,408,342	10,281,680	38.78	1,997,515.08	2,312,929.14	15.79	2,325,525.78	2010	16.42
Fiji	1,833,300	744,469	868,627	16.68	1,275,352.20	1,255,321.48	−1.57	1,255,321.48	2014–2015	−1.57
Haiti	2,775,000	7,319,493	10,695,542	46.12	392,020.34	391,097.16	−0.24	415,719.5	2004	6.05
Indonesia	190,456,900	258,383,256	187,739,786	−27.34	92,778,372.91	109,441,597.15	17.96	115,702,820	1993–2000	24.71
Jamaica	1,099,200	2,461,049	2,891,021	17.47	873,996.74	780,378.31	−10.71	780,378.31	2015	−10.71
Japan	37,791,500	125,331,291	127,985,133	2.12	26,054,153.73	25,346,524.97	−2.72	25,346,524.97	2015	−2.72
Martinique	112,800	362,757	378,478	4.33	81,823.50	81,404.43	−0.51	81,404.43	2015	−0.51
Mauritius	204,000	1,082,956	1,259,456	16.30	76,952.47	52,026.43	−32.39	52,026.43	2015	−32.39
Philippines	30,000,000	65,020,116	102,113,212	57.05	12,746,950.41	13,302,356.60	4.36	13,302,775.67	2014	4.36
Papua New Guinea	46,284,000	4,836,217	8,107,775	67.65	39,635,914.03	39,273,520.70	−0.91	38,638,884.42	2000	−2.52
Puerto Rico	1,380,000	3,469,068	3,381,518	−2.52	525,596.97	578,935.30	10.15	587,869.56	2009	11.85
Singapore	72,150	3,199,642	5,592,152	74.78	12,596.64	8667.02	−31.20	8667.02	2015	−31.20
Solomon	2,839,900	329,995	603,118	82.76	2,692,243.52	2,700,078.46	0.29	2,705,035	2008	0.48
Sri Lanka	6,561,000	17,736,821	20,908,027	17.88	2,573,668.68	2,317,502.56	−9.95	2,279,645.82	2004	−11.42
Taiwan	3,619,300	20,868,148	23,557,477	12.89	2,276,092.77	2,196,941.65	−3.48	2,196,941.65	2015	−3.48
Tasmania	6,840,100	474,224	516,600	8.93	5,447,865.03	5,360,824.30	−1.60	5,311,537.06	2000	−2.50
Vanuatu	1,219,900	155,170	271,130	74.73	887,030.68	1,138,101.05	28.30	1,138,101.04	2014–2015	28.30
Zanzibar	246,100	350,000	No data	No data	24,598.07	26,092.17	6.07	28,843.51	2004	17.26

Fig. 1. Net percentage change in forest cover for each island studied. The mean change in net forest cover across all islands was −3.132%, indicated by the dotted line.

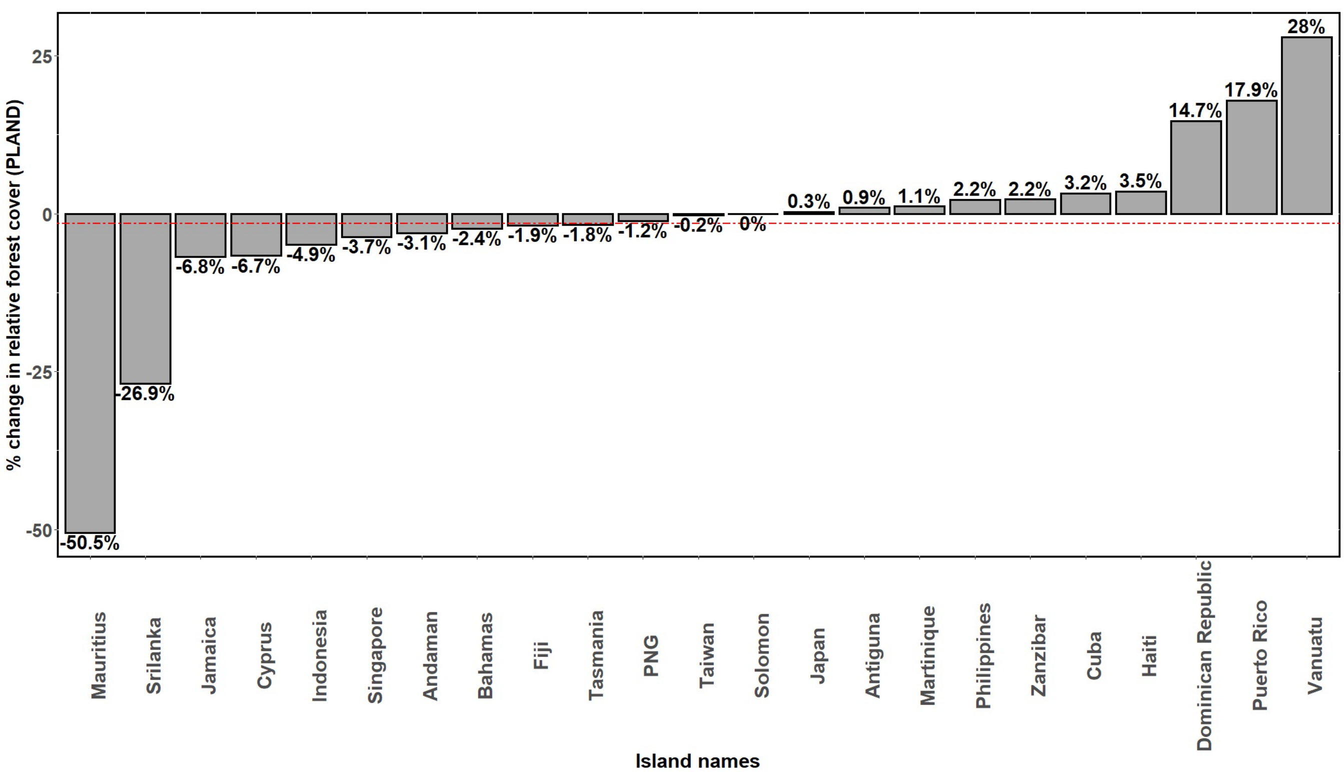

Fig. 2. Change trajectories of six net forest-cover metrics for three example islands (Japan, Singapore, and Papua New Guinea) over the four subperiods of our analysis from 1992–2015. These islands were grouped together in their forest-cover metrics (Fig. 3). This figure shows that even though the net change in forest cover remained low for some islands, the landscape configuration changed significantly, with potentially important implications for ecological processes that depend on connectivity.

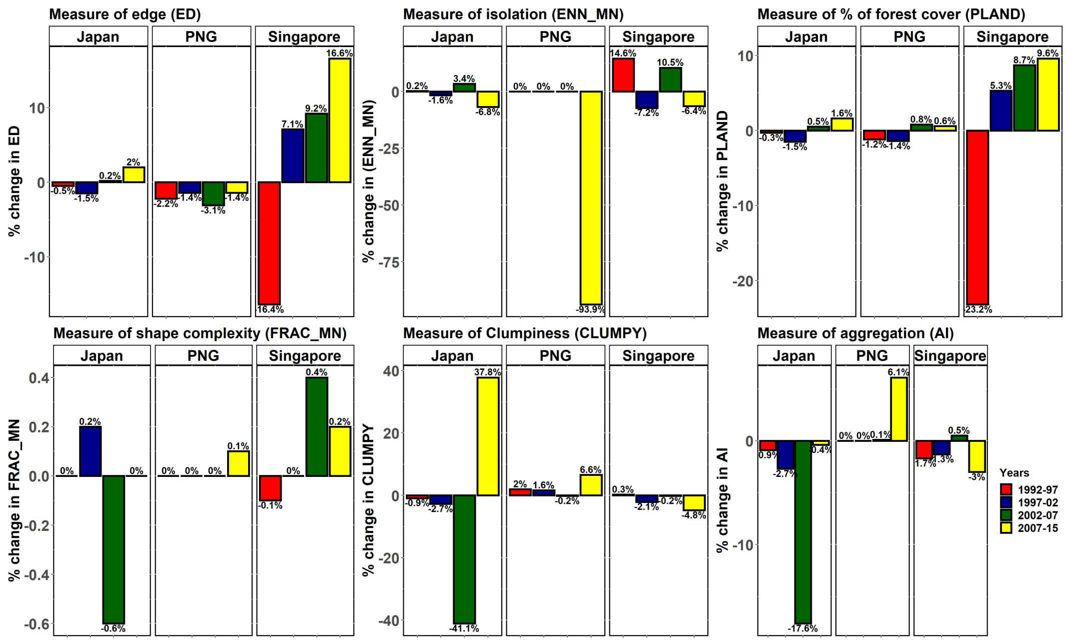

Fig. 3. Dendrogram showing hierarchical clusters that emerged from the relative forest-cover metrics (total area, as measured through percentage of forest cover). The similarities and dissimilarities between islands in relation to forest cover measures emerged as four stable clusters, where cluster members are more similar to one another than to other islands in the sample. This result illustrates the relative irrelevance of national-level gross domestic product as a predictor of trends in island forest composition and configuration. For example, the highly industrialized island of Japan shows similar trends to the much less industrialized nation of Papua New Guinea.

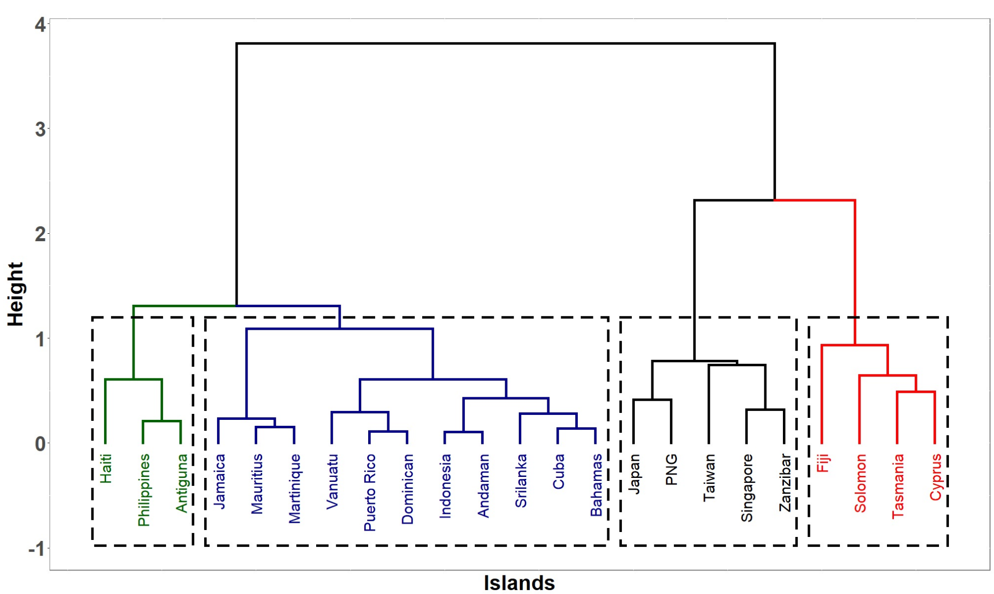

Table 5. Results of Mantel test correlations between matrices of landscape composition and configuration metrics and the economic growth drivers. To perform the test, we first produced temporally independent data for each variable and economic driver for each subperiod. Subject-subject dissimilarity matrices were then generated and compared using the Mantel test. Results with $P > 0.05$ are considered statistically significant. See Table 2 for metric definitions.

Metric	Population growth		Forest rents		Gross domestic product per capita		Human Development Index		Agriculture value added	
	r	*P*	*r*	*P*	*r*	*P*	*r*	*P*	*r*	*P*
PLAND	0.8303	0.0167	0.8182	0.0500	0.5030	0.0333	0.8667	0.0167	0.8788	0.0250
FRAC_MN	0.7697	0.0250	0.8303	0.0250	0.7333	0.0166	0.9515	0.0083	0.7697	0.0667
ED	0.7818	0.0250	0.6970	0.0667	0.4545	0.0667	0.9515	0.0083	0.8545	0.0167
CLUMPY	0.6606	0.0416	0.8424	0.0250	0.4303	0.0750	0.8788	0.0083	0.8788	0.0167
AI	0.7333	0.0333	0.7818	0.0583	0.4424	0.0583	0.8788	0.0167	0.9758	0.0083
ENN_MN	0.9030	0.0167	0.3818	0.1167	0.7697	0.0416	0.8667	0.0083	0.8788	0.0083

Table 6. Results of ANOVA tests of the hypothesis that groups based on gross domestic product growth should be the same as the forest-cover change groups. See Table 2 for metric definitions.

Metric used for clustering	Degrees of freedom	Sum of squares	Mean squares	*F*	*P*	Decision on statistical hypothesis
PLAND	2	179.4	89.70	22.68	< 0.05	Reject
	9	678.8	75.42	5.685	< 0.05	Reject
	5	1458	291.53	20.06	< 0.05	Reject
	3	8.2	2.723	0.182	> 0.05	Support
FRAC_MN	14	1813	129.50	14.47	< 0.05	Reject
	2	199.8	99.92	4.771	< 0.05	Reject
	1	87.6	87.55	4.082	< 0.05	Reject
	2	36.8	18.41	1.072	> 0.05	Support
ED	14	1173	83.78	6.898	< 0.05	Reject
	2	997.6	498.8	112.1	< 0.05	Reject
	3	144.6	48.21	3.396	< 0.05	Reject
CLUMPY	2	107.6	53.81	3.893	< 0.05	Reject
	6	404.6	67.43	3.807	< 0.05	Reject
	5	593.2	118.64	11.73	< 0.05	Reject
	8	1520	189.97	24.11	< 0.05	Reject
AI	8	1680	210.06	32.05	< 0.05	Reject
	1	102.7	102.69	12.48	< 0.05	Reject
	3	184.7	61.56	3.084	< 0.05	Reject
	7	616.8	88.12	5.175	< 0.05	Reject
ENN_MN	5	912.3	182.47	19.85	< 0.05	Reject
	4	483.7	120.92	17.34	< 0.05	Reject
	3	263.8	87.93	5.533	< 0.05	Reject
	7	630	89.96	5.218	< 0.05	Reject

approximately 2% in edge; largest decrease −0.64% in shape and −1.53% in edge). By contrast, both aggregation index and clumpiness changed significantly between 2002 and 2007, with declines of −17.6 and −41%, respectively. Japan, for example, showed a 37% increase in clumpiness in the period 2007–2015.

To assess the similarities and dissimilarities between islands in relation to economic variables, we performed Mantel tests using landscape metrics and economic drivers for the corresponding islands. The Mantel test comparing economic variables and meso-scale land use (Table 5) showed that for 4 of 30 instances, the null hypothesis was supported (e.g., forest rents and forest cover had Mantel statistics $r = 0.8182$ and $P = 0.05$); for the others, the null hypothesis was rejected (e.g., comparison of GDP per capita and clumpiness gave $r = 0.4303$ and $P = 0.0750$).

To assess the similarities and dissimilarities between islands in relation to GDP growth, we grouped the islands by similarities in their landscape metrics (Fig. 3). This unsupervised clustering analysis indicated that there were four natural clusters of islands ($k = 4$) for most metrics. Clusters represented groupings of islands that were more similar to each other than to other islands, providing an unbiased taxonomy of islands that was independent of their economic data. Islands did not fall in the same clusters for all metrics, indicating a lack of consistency in their forest-cover trajectories. The ANOVA test of whether national economic variables and meso-scale land use were interrelated (Table 6) showed that for 2 of 23 instances, the null hypothesis was supported; for the others, the null hypothesis was rejected. In addition, the correlation between forest area and GDP was weak (Spearman $\rho = -0.19$, $P < 0.37$). We thus found no clear relationship between change in forest cover and economic growth.

Finally, comparison of the log of absolute island area to changes in population density, forest area, and forest patch sizes yielded no significant correlations (df = 3, sums of squares = 8181, F = 12, $P < 0.0001$), indicating that our results are not an artefact of considering relative rather than absolute changes in forest cover.

DISCUSSION AND CONCLUSION

In stark contrast with most global deforestation analyses (Achard et al. 2002, Hansen et al. 2008, 2013, DeFries et al. 2010, Song et al. 2018), consideration of forest-cover change patterns and trends at a meso-scale level of analysis did not provide a clear separation of countries based on economic data. We found four broad composition and configuration clusters within geographically and socioeconomically heterogeneous islands with varied forest cover, although the membership of each cluster was not consistent for every forest-related metric. Island groups as defined by forest-cover change contained mixed economic and socioeconomic types and were geographically diverse. These results paint a more complex picture than do coarser global land-cover change analyses and suggest strong scale dependence in current understanding of the relationships between forest cover and economic activity. The lack of general trends is intriguing and suggests that important processes and dynamics have not been adequately included in existing theories of deforestation; hence, islands appear to offer an interesting and potentially feasible entry point for further research linking fine- and broad-scale drivers of deforestation.

Although local and meso-scale land-use trends are influenced by national and global trends (Geist and Lambin 2002), they may differ substantially from them. For 4 of 30 instances (Mantel test, Table 5) and for 2 of 23 instances (ANOVA test, Table 6), our null hypothesis was supported (e.g., for forest cover), whereas for other instances it was rejected (e.g., for edge density), providing no clear evidence to support a relation between landscape metrics and drivers of economic growth. Forest-cover change and economic growth should be strongly correlated if composition and configuration metrics were directly influenced by economic growth (Crespo Cuaresma et al. 2017), implying that national-level economic trends alone are not sufficient to explain deforestation. In simple terms, our data show that wealth alone does not drive forest conservation and that developing countries are not necessarily poor stewards of forests, despite their proportionally higher economic dependence on forests. For larger nations, simplistically comparing national-level economic indicators with deforestation per se through remote sensing ignores the meso-scale dynamics of markets, access, and settlement patterns that can strongly influence forest loss and gain and economic growth patterns. Many authors (Cropper and Griffiths 1994, Angelsen and Kaimowitz 1999, Lykke et al. 2002, DeFries et al. 2010) have highlighted the demographic, policy, and economic factors that contribute to growing demands for agriculture, rangeland, and wood that in turn exert pressure on forests, but the degree to which these influences are relevant across different scales has been less clear. Encouragingly, it appears that effective forest cover can be maintained across a wide variety of national-level economic conditions. Our results thus provide additional novel empirical support for recent calls for stronger development of mid-range, contextualized theory (Magliocca et al. 2018, Meyfroidt et al. 2018).

Configuration metrics describe additional impacts of forest loss and fragmentation on ecological processes and ecosystem services. Despite the ongoing debate in conservation biology about the relative importance of habitat composition and habitat configuration (Fletcher et al. 2018, Fahrig et al. 2019, Miller-Rushing et al. 2019), there is good evidence that habitat fragmentation matters for a wide range of ecological processes (Cunningham et al. 2015, Haddad et al. 2015). Interestingly, for some islands in our analysis, landscape configuration indices changed much more than composition indices, suggesting subtle differences in the ways in which forests are used. These changes are again largely undetectable at global scales of analysis, supporting the argument that meso-scale analyses of landscape change provide a potentially useful way of linking global and local drivers of change.

Differences in the results obtained by forest-cover analyses at different scales have potentially important consequences for forest policy and conservation efforts. For example, Le et al. (2012) found that most forest conservation policies focus on area planted and initial tree survival for short-term biodiversity restoration or timber production, whereas broader criteria for longer term success and sustainability are ignored. Treby et al. (2014) also found significant gaps between global, national, state, and territorial forest management plans; and Decocq et al. (2016) found that small patches were generally not legally protected against conversion to another land use. Long-term changes in global forest cover are well documented and may be used to design policies governing forest management and land use (e.g., reforestation and afforestation policies).

Looking forward, theory suggests that incongruities between the scales of forest management policy design and implementation can result in poor forest management and conservation (Epstein et al. 2015). Our analysis highlights the point that one of the central questions for efforts to sustainably govern forests will be that of how to align different policies and forest initiatives at different scales (national, regional, and local) in ways that are both effective within scales and consistent across scales. Understanding the drivers of both deforestation and afforestation at different scales will in turn require the deliberate measurement and cross-case comparison of relevant influences on deforestation, ranging from national policies through regional governance structures to local regulations and guidelines. Obtaining these data will require that social scientists in particular step out of their standard paradigm (i.e., in-depth study at a single location) and, instead, compare trends across multiple study locations from different systems that are distinct at regional and national as well as local scales (Cumming et al. 2020). Consideration of islands and the ways in which they can be used to understand how local and national scales of policy are interrelated may thus offer important new insights for developing more effective forest conservation policies.

Responses to this article can be read online at:
http://www.ecologyandsociety.org/issues/responses.php/11713

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Data Availability Statement:

The data that support the findings of this study are openly available in world development indicators. The data were obtained from the World Bank Open Data Set (https://data.worldbank.org/). Global land-cover data generated under the Climate Change Initiative are available through http://cci.esa.int/content/land-cover-data and following the methods of Santoro et al. (2017). To calculate dendrogram clusters we used the TSClust library in R, and for enhanced visualization of dendrograms, we used the factoextra library in R. For other calculations and analyses, usual R libraries and packages were used and cited.

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Appendix 1

Table S.1. Legends used in the LC maps. The time series data were grouped into the six broad land categories, i.e. cropland, forest, grassland, wetland, settlement and other land. The class ‘other land’ is further described as shrubland, sparse vegetation, bare area and water.

Classes	LC value	Label
Agriculture	10, 11, 12	Rain-fed cropland
Agriculture	20	Irrigated cropland
Agriculture	30	Mosaic cropland (> 50%)/natural vegetation (tree, shrub, herbaceous cover) (< 50%))
Agriculture	40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (< 50%)
Forest	50	Tree cover, broadleaved, evergreen, closed to open (>15%)
Forest	60, 61, 62	Tree cover, broadleaved, deciduous, closed to open (> 15%)
Forest	70, 71, 72	Tree cover, needle-leaved, evergreen, closed to open (> 15%)
Forest	80, 81, 82	Tree cover, needle-leaved, deciduous, closed to open (> 15%)
Forest	90	Tree cover, mixed leaf type (broadleaved and needle-leaved)
Forest	100	Mosaic tree and shrub (>50%) / herbaceous cover (< 50%)
Forest	160	Tree cover, flooded, fresh or brakish water
Forest	170	Tree cover, flooded, saline water
Grassland	110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
	130	Grassland
Wetland	180	Shrub or herbaceous cover, flooded, fresh-saline or brakish water
Settlement	190	Urban
Other,	120—122	Shrubland
Sparse	140	Lichens and mosses
Vegetation	150—153	Sparse vegetation (tree, shrub, herbaceous cover)

Bare area	200—202	Bare areas
Water	210	Water

Table S.2. Summary data for the economic variables, forest rents (% GDP), agriculture (and forestry, and fishing) value added (% of GDP), and HDI with forest cover for each island

Island	Forest rents (% of GDP)		Agriculture, forestry, and fishing, value added (% of GDP)		HDI	
Name	1992	2015	1992	2015	1992	2015
Anadaman and Nicobar	0.614	0.302	26.67	16.174	0.44	0.63
Antigua and Barbuda	*No data*	*No data*	1.803	1.6123	*No data*	0.77
Bahamas	*No data*	*No data*	2.663	0.821	*No data*	0.80
Cuba	0.231	0.084	12.427	3.835	0.66	0.77
Cyprus	0.011	0.009	5.724	1.8629	0.74	0.86
Dominican Republic	0.056	0.048	12.013	5.485	0.61	0.73
Fiji	0.470	0.756	17.583	7.872	0.65	0.72
Haiti	1.167	0.946	34.121	17.417	0.42	0.49
Indonesia	1.318	0.523	19.521	13.493	0.53	0.70
Jamaica	0.351	0.205	*No data*	6.309	0.65	0.72
Japan	0.018	0.015	*No data*	1.114	0.82	0.91
Martinique	*No data*	*No data*	*No data*	*No data*	*No data*	*No data*
Mauritius	0.020	0.001	10.0127	3.154	0.63	0.79
Philippines	0.58	0.265	21.821	10.260	0.6	0.70
Papua New Guinea	3.771	2.711	25.979	17.457	0.39	0.54
Puerto Rico	*No data*	*No data*	1.2128	0.827	*No data*	*No data*
Singapore	0.001	0.000	0.197	0.0326	0.74	0.93
Solomon	7.310	21.48	44.414	*No Data*	*No data*	0.55
Sri Lanka	0.508	0.122	26.122	8.184	0.63	0.77
Taiwan	0.001	0.002	21.329	8.422	0.52	0.74

Tasmania	0.188	0.119	3.053	2.373	0.87	0.93
Vanuatu	0.903	0.814	16.20	25.842	*No data*	0.60
Zanzibar	11.114	3.994	44.704	26.746	0.37	0.52

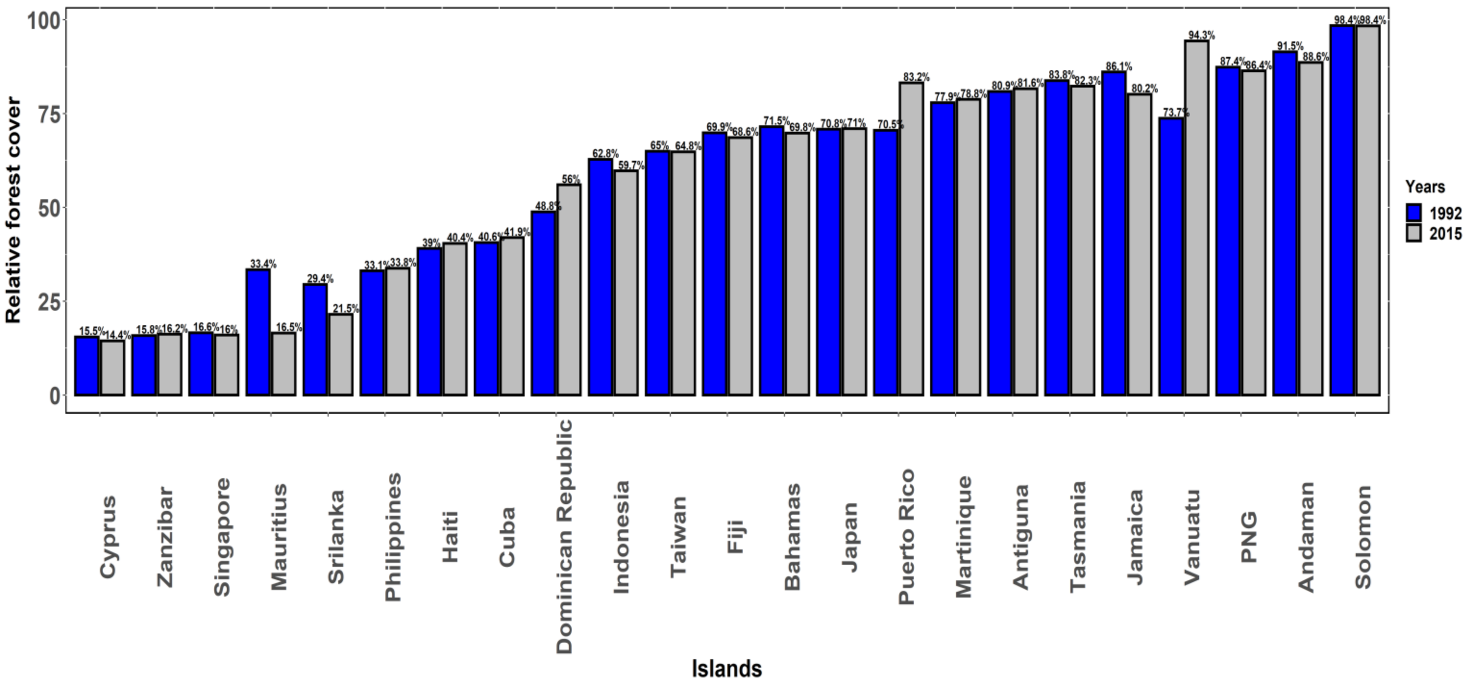

Fig. A.1 Forest relative cover for each island for the years 1992 and 2015 (used to determine percentage net forest change (Figure 1)).