Humid tropical forest clearing from 2000 to 2005 quantified by using multitemporal and multiresolution remotely sensed data

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Forest cover is an important input variable for assessing changes to carbon stocks, climate and hydrological systems, biodiversity richness, and other sustainability science disciplines. Despite incremental improvements in our ability to quantify rates of forest clearing, there is still no definitive understanding on global trends. Without timely and accurate forest monitoring methods, policy responses will be uninformed concerning the most basic facts of forest cover change. Results of a feasible and cost-effective monitoring strategy are presented that enable timely, precise, and internally consistent estimates of forest clearing within the humid tropics. A probability-based sampling approach that synergistically employs low and high spatial resolution satellite datasets was used to quantify humid tropical forest clearing from 2000 to 2005. Forest clearing is estimated to be 1.39% (SE 0.084%) of the total biome area. This translates to an estimated forest area cleared of 27.2 million hectares (SE 2.28 million hectares), and represents a 2.36% reduction in area of humid tropical forest. Fifty-five percent of total biome clearing occurs within only 6% of the biome area, emphasizing the presence of forest clearing "hotspots." Forest loss in Brazil accounts for 47.8% of total biome clearing, nearly four times that of the next highest country, Indonesia, which accounts for 12.8%. Over three-fifths of clearing occurs in Latin America and over one-third in Asia. Africa contributes 5.4% to the estimated loss of humid tropical forest cover, reflecting the absence of current agro-industrial scale clearing in humid tropical Africa.

deforestation | humid tropics | remote sensing | change detection | monitoring

Quantifying rates of humid tropical forest cover clearing is critical for many areas of earth system and sustainability science, including improved carbon accounting, biogeochemical cycle and climate change modeling, management of forestry and agricultural resources, and biodiversity monitoring. Concerning land cover dynamics, humid tropical forest clearing results in a large loss of carbon stock when compared with most other change scenarios. The humid tropical forests are also the site of considerable economic development through direct forestry exploitation and frequent subsequent planned agro-industrial activities. The result is that tropical forests and their removal feature prominently in the global carbon budget (1). In addition, the humid tropics include the most biodiverse of terrestrial ecosystems (2), and the loss of humid tropical forest cover results in a concomitant loss in biodiversity richness.

Assessing the dynamics of this biome is difficult because of its sheer size and varying level of development within and between countries. To date, there is no clear consensus on the trends in forest cover within the humid tropics. Grainger (3) illustrated this point mainly through the use of data from the Food and Agriculture Organization of the United Nations Forest Resource Assessments (4–6) and consequently emphasized the need for improved monitoring programs. A practical solution to examining trends in forest cover change at biome scales is to employ remotely sensed data. Satellite-based monitoring of forest clearing can be implemented consistently across large regions at a fraction of the cost of obtaining extensive ground inventory data. Remotely sensed data enable the synoptic quantification of forest cover and change, providing information on where and how fast forest change is taking place. Various remote-sensing-based methods have been prototyped within this biome (5, 7–11) and combined with information on carbon stocks to estimate carbon emissions (8, 12, 13). The method presented here advances the science of monitoring forest cover change by employing an internally consistent and efficient probability-based sampling approach that synergistically employs low- and high-spatial-resolution satellite datasets. The results represent a synoptic update on rates of forest clearing within the humid tropics since 2000. For this study, forest clearing equals gross forest cover loss during the study period without quantification of contemporaneous gains in forest cover due to reforestation or afforestation. The method presented could be implemented repeatedly for both forest cover loss and gain in establishing internally consistent biome-scale trends in both gross and net forest cover loss and/or gain.

Moderate spatial resolution (250 m, 500 m, and 1 km) data from the MODerate Resolution Imaging Spectroradiometer (MODIS) are imaged nearly daily at the global scale, providing the best possibility for cloud-free observations from a polar-orbiting platform. However, MODIS data alone are inadequate for accurate change area estimation because most forest clearing occurs at sub-MODIS pixel scales. High-spatial-resolution Landsat data (28.5 m), in contrast, do allow for more accurate measurement of forest area cleared. However, because of infrequent repeat coverage, frequent cloud cover, and data costs, the use of Landsat data for biome-scale mapping is often precluded. Integrating both MODIS and Landsat data synergistically enables timely biome-scale forest change estimation.

We used MODIS data to identify areas of likely forest cover loss and to stratify the humid tropics into regions of low, medium, and high probability of forest clearing. A stratified random sample of 183 18.5-km × 18.5-km blocks taken within these

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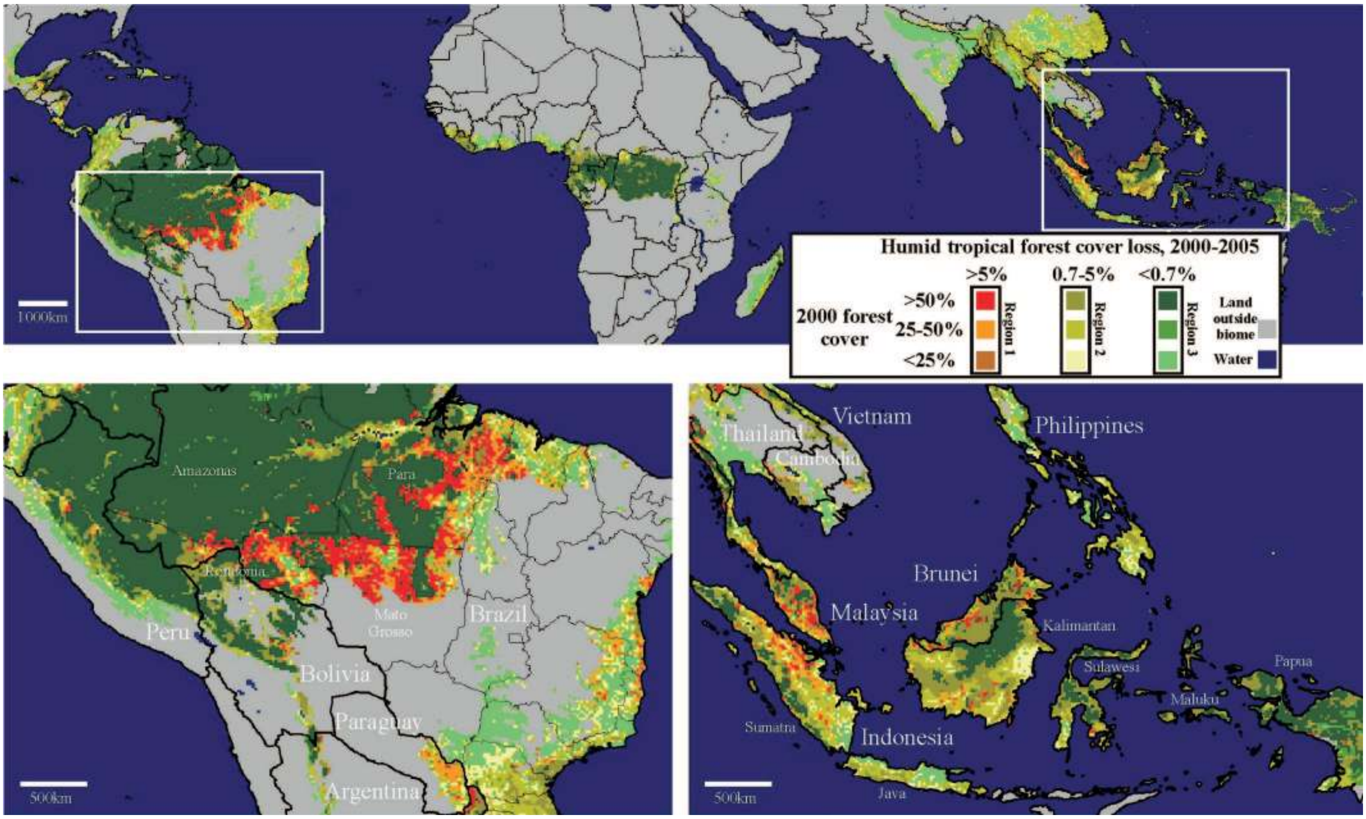

Fig. 1. Forest clearing and forest cover in the humid tropical forest biome, 2000–2005. Total forest clearing over the study period is estimated to be 27.2 million hectares (SE 2.28 million hectares). Regional variation in clearing intensity is shown: Region 1 covers 6% of the biome and contains 55% of clearing; region 2 covers 44% of the biome and contains 40% of forest clearing; and region 3 covers 50% of the biome and contains 5% of forest clearing. Data from this figure are available at http://globalmonitoring.sdstate.edu/projects/gfm.

regions was interpreted for forest cover and forest clearing by using high-spatial-resolution Landsat imagery from 2000 and 2005. Typically, Landsat imagery has been used to provide regional forest area change estimates because its sufficiently high spatial resolution enables the detection of most forest clearing events (11, 14, 15). Consistent with this practice, our estimates of forest clearing are based on interpreting Landsat imagery for the 183 sample blocks selected. Our sampling strategy differs from previous efforts (5, 8) in that we took advantage of forest clearing information available from independent imagery, the MODIS change indicator maps, to define strata and to construct regression estimators of forest clearing.

Results

Our results reveal that rates of clearing in the biome remain comparable with those observed in the 1990s (5, 8, 9). Forest clearing is estimated to be 1.39% (SE 0.084%) of the total biome area. This translates to an estimated forest area cleared of 27.2 million hectares (SE 2.28 million hectares) and represents a 2.36% reduction in year-2000 forest cover. Fig. 1 depicts the spatial variation in gross forest cover loss from 2000 to 2005. The biome can be divided into three regions of forest clearing intensity. The first region consists of areas with >5% clearing per block and largely captures the current centers of agro-industrial scale clearing in South America and Insular Southeast Asia. Of the total biome area cleared, 55% occurs in this region that constitutes only 6% of the biome area, illustrating the presence of forest clearing "hotspots" (region 1 in Fig. 1). The second region of 0.7–5% clearing per block constitutes 44% of the biome area. This region consists of less spatially concentrated clearing and accounts for 40% of all clearing within the biome. The other 5% of forest clearing is found within a third region consisting of the remaining predominantly intact forest zones (35% of the biome area) and areas largely deforested before 2000 (15% of the biome area).

Our findings emphasize the predominance of Brazil in humid tropical forest clearing (Table 1). By area, Brazil accounts for 47.8% of all humid tropical forest clearing, nearly four times that of the next highest country, Indonesia, which accounts for 12.8% of the total. Over three-fifths of clearing occurs in Latin America and over one-third in Asia. Forest clearing as a percentage of year-2000 forest cover for Brazil (3.6%) and Indonesia (3.4%) exceeds the rest of Latin America (1.2%), the rest of Asia (2.7%), and Africa (0.8%). Beyond the arc of deforestation in Brazil, Latin American hotspots include northern Guatemala, eastern Bolivia, and eastern Paraguay. As a percentage of year-2000 forest cover, Paraguay features the highest areal proportion of change hotspots, indicating an advanced, nearly complete forest clearing dynamic. Indonesian island groups of Sumatra, Kalimantan, Sulawesi, and Papua feature varying degrees of forest removal, with Sumatra the site of the most intense recent large-scale clearing and Papua a measurable but low level of forest clearing. Riau province in Sumatra has the highest indicated change within Indonesia. Hot spots of clearing are present in every state of Malaysia, and clearing in Cambodia along its border with Thailand is among the highest of indicated change hot spots. Africa, although a center of widespread, low-intensity selective logging (16), contributes only 5.4% to the estimated loss of humid tropical forest cover. This result reflects the absence of current agro-industrial scale clearing in humid tropical Africa.

Our results reveal a higher degree of regional variation in forest clearing than currently portrayed by the only other source

Table 1. Regional estimates of humid tropical forest area cleared

Region	Percent of biome area	Percent contribution of region to forest loss in the biome	Within-region forest loss as percent of land area (SE)	Within-region forest loss as percent of year 2000 forest area	Blocks sampled
Brazil	27.09	47.8	2.45 (0.14)	3.60%	53
Americas sans Brazil	21.27	12.6	0.82 (0.13)	1.23	10
Indonesia	9.16	12.8	1.95 (0.20)	3.36	77
Asia sans Indonesia	27.60	21.4	1.08 (0.33)	2.68	31
Africa	14.88	5.4	0.50 (0.13)	0.76	12
Pan-Americas	48.36	60.4	1.73 (0.10)	2.56	63
Pan-Asia	36.76	34.3	1.29 (0.25)	2.90	108
Biome total	100	100	1.39 (0.084)	2.36	183

of information for the pan-tropics during the study period, the 2005 Forest Resource Assessment (FRA) report from the Food and Agriculture Organization of the United Nations (6). The FRA 2005 report highlights Africa and South America as having the highest rates of forest area loss, both in excess of 4 million hectares per year. For those African countries predominantly within the humid tropics, our humid-tropics-only estimate is less than one-third of the FRA estimate. For both this study and the FRA, Brazil and Indonesia are the countries featuring the highest forest clearing rates. However, our results differ as to the relative magnitude of change. For Brazil and Indonesia, the FRA reports annual change in forest area from 2000 to 2005 equal to 3.10 and 1.87 million ha/yr, respectively (6). Our estimates of forest clearing for Brazil and Indonesia are 2.60 and 0.70 million ha/yr, respectively. The results for Indonesia represent a dramatic decrease from 1990 to 2000 clearing rates.

Discussion

Our strategy incorporating the MODIS-derived forest clearing information in both the sampling design (stratification) and estimation (regression estimator) components of the monitoring strategy yielded the requisite precision and cost efficiency desired for an operational monitoring protocol at the pan-tropical scale. The standard error we obtained for the biome-wide estimated forest loss of the humid tropics was comparable with those reported by the Food and Agriculture Organization of the United Nations in 2000 (5) and Achard *et al.* (8), but we were able to achieve this level of precision with much smaller sample coverage. The total area of Landsat imagery sampled in our study was 0.21% of the biome, whereas previous studies (5, 8) used samples covering 10% and 6.5% of the tropical domain. Our sampling strategy thus yields precise estimates of forest clearing based on an areal sample coverage that could be sustainable from an effort and cost standpoint for future monitoring goals. Our approach is readily adaptable to other high-spatial-resolution sensors because the success of the strategy derives from advantageously incorporating the MODIS data in both the sampling design and analysis components.

Considerable debate on the appropriate use of Landsat data for regional monitoring has concerned the alternative uses of exhaustive mapping versus sampling-based approaches (17–19). Data limitations, namely cloud cover and costs of imagery, have been the principal arguments against exhaustive mapping. The challenge to a sampling approach is that change is typically rare at the scale of a biome. Consequently, a critical requirement for obtaining precise sample-based estimates is to construct strata that effectively identify areas of intensive forest clearing. The use of expert opinion to delineate broad regions of suspected change has been used to achieve this end (8). In contrast, we implemented a more spatially targeted approach to stratification, using MODIS imagery to flag areas of likely forest clearing. The MODIS imagery allowed assigning each 18.5-km × 18.5-km block in the biome individually to a stratum, thus improving on the broader regional strata used previously (8). Furthermore, MODIS imagery allows for the identification of clearing on an annual basis and therefore provides a more temporally resolved view of change than possible with Landsat data alone.

An additional criticism of the sampling approach is the absence of a spatial representation of where in the biome forest clearing is occurring. We address this concern by applying the stratum-specific regression models relating Landsat-derived clearing to MODIS-derived clearing at the support of the 18.5-km × 18.5-km blocks to predict clearing for each block (Fig. 1). This spatial depiction of forest clearing takes advantage of the respective strengths of the complete coverage MODIS imagery and the high spatial resolution of the Landsat imagery. The more frequent temporal coverage of the MODIS imagery alleviates the problem of cloud cover obscuring tropical areas during the few available Landsat overpasses (20). Calibrating the MODIS-derived clearing values based on the Landsat-derived clearing observed on the sample blocks compensates for the inability of the larger MODIS pixel size (500 m) to detect smaller areas of clearing that are observable from the 28.5-m Landsat pixels. Although area estimates derived from coarser-resolution data are commonly calibrated by using a nonrandom sample of high-resolution data (21, 22), a strength of our approach is that by implementing a probability sampling design to collect the

Table 2. Stratified sampling design

MODIS change (≥90%)	Humid tropics (excluding Indonesia): Stratum no.	Humid tropics (excluding Indonesia): No. of blocks sampled	Humid tropics (excluding Indonesia): Percent of stratum sampled	Indonesian humid tropics: Stratum no.	Indonesian humid tropics: No. of blocks sampled	Indonesian humid tropics: Percent of stratum sampled
0–2%	1A	21	0.08	5A	8	0.51
	1B	25	0.12	5B	33	1.17
2–9%	2	23	1.76	6	17	9.24
>9%	3	32	8.10	7	18	26.09
—	4 (certainty)	5	100	8 (certainty)	1	100

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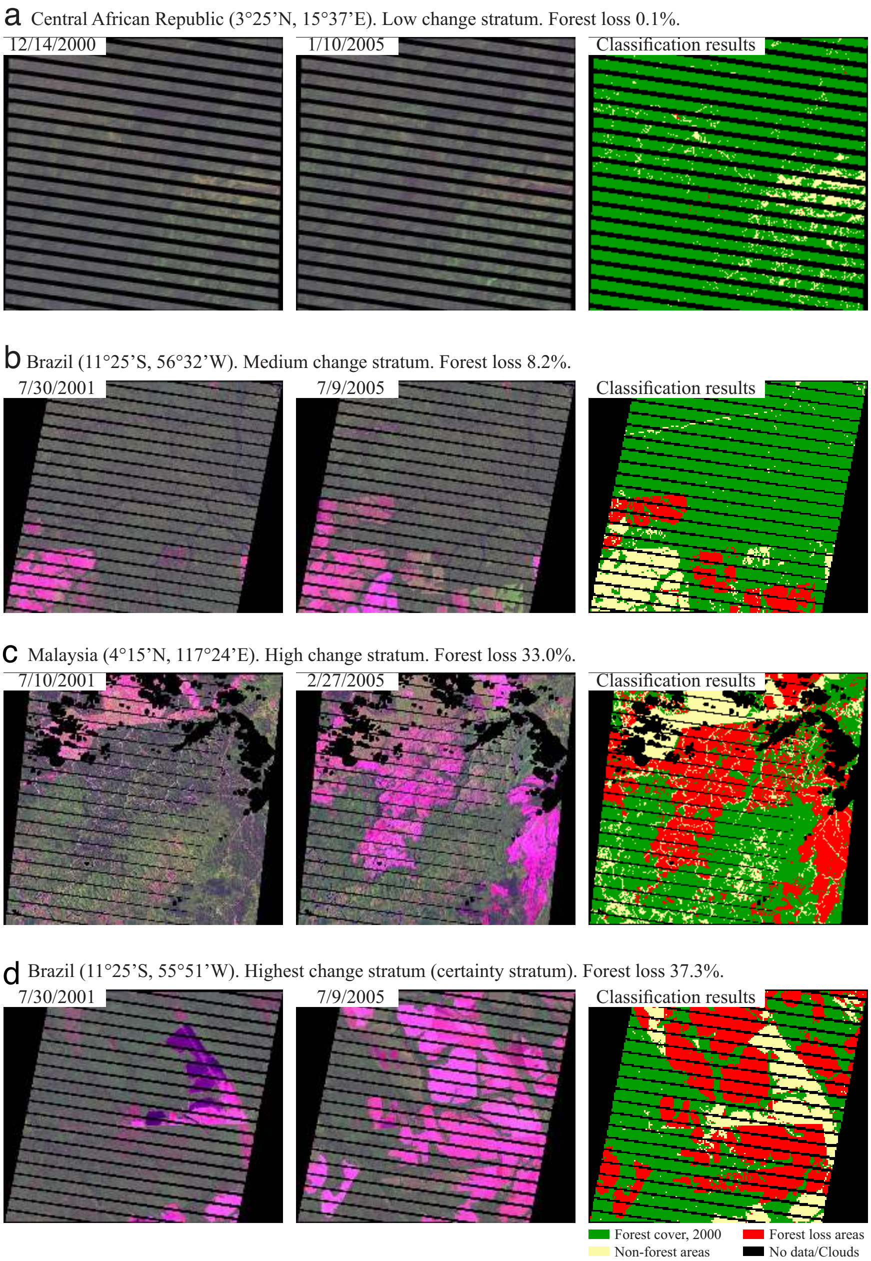

Fig. 2. Examples of Landsat sample blocks characterized to estimate forest cover and change from 2000 to 2005. Each block covers 18.532 km per side and has been reprojected into local Universal Transverse Mercator coordinates. The strata are created by using the biome-wide MODIS 2000 to 2005 forest clearing probability maps. (*a*) Sample block from the MODIS change strata 1 and 5. (*b*) Sample block from MODIS change strata 2 and 6. (*c*) Sample block from MODIS change strata 3 and 7. (*d*) Sample block from MODIS change certainty strata 4 and 8. All blocks used in this analysis can be viewed at http://globalmonitoring.sdstate.edu/projects/gfm.

sample of high-resolution data, we retain the rigorous design-based inference framework (23) to support the statistical validity of our estimates. Furthermore, by construction, the aggregate predicted change over any defined subregion of the biome (Table 1) equals the estimated forest cover loss derived from the sample blocks, thus ensuring internal consistency between the mapped (Fig. 1) and estimated forest loss.

The results of this analysis highlight the need for internally consistent biome-scale monitoring to accurately depict relative variations in forest clearing dynamics within and between countries. Results from national-scale studies that employ varying methods, definitions, and input data may result in incompatible products that preclude regional syntheses (24). Biome-scale forest cover and change estimates derived from remotely sensed data offer a way forward for monitoring forests in support of both basic earth science research and policy formulation and implementation. For example, these results could be combined with information on carbon stocks to support carbon accounting programs such as the "Reducing Emissions for Deforestation and Degradation" (REDD) initiative (25). Such an approach could be implemented at both national and regional scales for the synoptic assessment of forest cover change and the monitoring of intra- or international displacement, or leakage, of forest cover clearing.

Although forest resources are a key component of economic development in this biome, forest governance is greatly hindered by a lack of timely information on change within the forest domain. A monitoring strategy combining data from sensors at multiple temporal and spatial resolutions offers a feasible and cost-effective methodology to produce timely, precise, and internally consistent estimates of biome-wide forest clearing for 5-year updates, and even annual updates for areas where rapid forest clearing is taking place (i.e., South America).

Methods

The humid tropical forest biome was delineated by using the World Wildlife Fund ecoregions map (26) as the primary reference. Biome-wide forest change indicator maps were created by using annual MODIS imagery for 2000–2005. We used a classification tree bagging algorithm (27) to produce per MODIS pixel annual and 4- and 5-year change probability maps within the humid tropics. MODIS 32-day composites were used as inputs and included data from the MODIS land bands (blue, 459–479 nm; green, 545–565 nm; red, 620–670 nm; near infrared, 841–876 nm; and mid infrared, 1230–1250, 1628–1652, and 2105–2155 nm) (28), as well as data from the MODIS Land Surface Temperature product (29). To produce a more generalized annual feature space that enabled the extension of spectral signatures to regional and interannual scales, the 32-day composites were transformed to multitemporal annual metrics. Annual metrics capture the salient features of phenological variation without reference to specific time of year and have been shown to perform as well or better than time-sequential composites in mapping large areas (30, 31). For each annual and 4- and 5-year interval, a total of 438 image inputs were used (146 metrics per year plus their calculated differences). The classification tree bagging algorithm related the expert-interpreted forest cover loss and no loss categories to the MODIS inputs. We applied a threshold to the annual and 4- and 5-year forest cover loss maps at various change probability values to produce per-500-m pixel forest change/no change maps. For each map, the 500-m pixel data were aggregated to produce a percent cover loss value (threshold dependent) for each block in the biome.

Standard error calculations based on ancillary data from another tropical deforestation study (9) led to the decision to use square sample blocks of 18.5 km per side grouped into strata (0–2%, 2–9%, and >9% forest clearing) as defined by the MODIS change indicator map using a threshold that corresponds to 90% probability [see supporting information (SI) Figs. S1 and S2]. The sample was further stratified geographically as resources were available to prototype the methodology for Indonesia before biome-wide implementation. The three MODIS-defined strata were used in both the Indonesian tropics and in the tropics outside of Indonesia (Table 2). The sample size allocated per stratum was initially determined by optimal allocation (32) but was modified slightly to obtain more sample blocks in the high forest loss strata. The six blocks with the highest MODIS-derived forest loss were placed in a certainty stratum. The effectiveness of the MODIS-change-based stratification can be quantified by estimating the ratio of the standard error of a simple random sample to the standard error for our stratified random sample (32). For Indonesia, this ratio was 2.04, and for the rest of the tropics, this ratio was 1.16, indicating a considerable advantage of stratification for Indonesia, and a modest advantage for the rest of the tropics.

Each Landsat sample block was classified by using a supervised decision tree classifier (33) to yield 2000 forest cover and 2000–2005 forest clearing areas. Each block was examined in detail by one or more interpreters, and the procedure was iterated if necessary, including manual editing where required, to achieve accurate per block depictions of forest cover and forest clearing. Forest was defined as >25% canopy cover, and change was measured without regard to forest land use. All tree cover assemblages that met the 25% threshold, including intact forests, plantations, and forest regrowth, were defined as forests. Sample block imagery and characterizations from each of the generic low, medium, high, and certainty strata are shown in Fig. 2. Missing data per sample block consisted of hand interpreted cloud and shadow cover and data gaps from the Landsat 7 Scan Line Corrector-Off (SLC-off) malfunction. To produce the within-biome forest cover values shown in Fig. 1, MODIS Vegetation Continuous Field (VCF) tree cover products (30) for the year 2000 were regressed against the forest masks derived for the Landsat block samples and extrapolated for all blocks within the biome.

Within original strata 1 and 5, poststratification was implemented to partition blocks into poststrata representing areas of near-zero change and areas of some change. The poststratification used data from the Intact Forest Landscapes (IFL) project (34) and the VCF tree cover map (30). Blocks that had

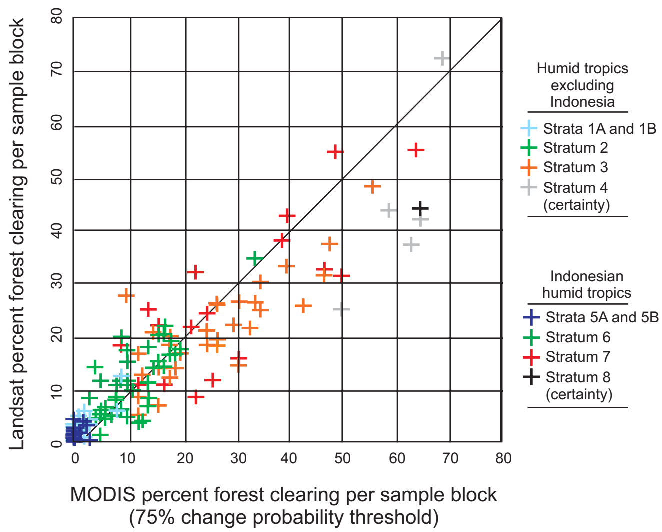

Fig. 3. Landsat and MODIS change comparison for the 183 sample blocks analyzed.

>25% IFL or <20% VCF tree cover, and a 90% MODIS threshold change value of 0% were placed in poststrata 1A and 5A (areas expected to show virtually no change), and the remaining blocks were placed in poststrata 1B and 5B.

Fig. 3 illustrates the relationship between the expert-interpreted Landsat block change and the operationally implemented MODIS block change, using a 75% change probability threshold. For each stratum, a separate regression estimator (32) was used in the analysis to estimate Landsat-derived forest area loss. The simple linear regression model applied to strata 2, 3, 5B, 6, and 7 used the MODIS 75% threshold data as the explanatory variable (y axis of Fig. 3). A two-variable linear model was applied to stratum 1B that used both the MODIS 75% and 90% threshold data. A regression estimator was not applied to strata 1A and 5A because these poststrata had very little change. Therefore, for these strata the estimates were based on the sample mean Landsat-derived clearing. The models selected were the best or nearly best fitting models evaluated for a suite of auxiliary variables that included MODIS-derived forest loss based on different thresholds and forest cover variables. Each model was applied per stratum and then aggregated to derive biome-scale forest clearing estimates. Subregional estimates were calculated for the three continents and for Brazil and Indonesia, all of which had enough samples to yield estimates of forest clearing with reasonable standard errors. Three other subregions (Fig. 1) were defined based on per block clearing thresholds to highlight biome-scale variations in clearing intensity.

Sample blocks were processed in a randomly ordered sequence. A sample was excluded if the Landsat data exhibited seasonal offsets or image misregistration, or if <25% of the block had useable data (area unaffected by SLC-off data gaps and cloud cover). In any of these cases, the next sample block in the randomly ordered list was processed. Just over 10% of samples did not meet the analysis criteria. The number of blocks excluded by stratum and by region and the distribution of the percent useable data for the blocks included in the sample are documented in Table S1. To evaluate possible biases introduced by having to exclude cloud-covered blocks, the MODIS change probability and IFL data were used to construct regression imputed values (23) for the excluded blocks. The forest loss estimates were recomputed by using weighted means derived from the observed sample values and the imputed values (for each stratum). For the full biome, the estimated forest loss incorporating the imputed values was 1.35%, compared with the reported estimate of 1.39%. For Indonesia, including the regression imputed values resulted in an estimated forest loss of 1.91%, compared with the reported estimate of 1.95%.

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