

Using indigenous knowledge to link hyper-temporal land cover mapping with land use in the Venezuelan Amazon: “The Forest Pulse”

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Abstract: Remote sensing and traditional ecological knowledge (TEK) can be combined to advance conservation of remote tropical regions, e.g. Amazonia, where intensive *in situ* surveys are often not possible. Integrating TEK into monitoring and management of these areas allows for community participation, as well as for offering novel insights into sustainable resource use. In this study, we developed a 250 m resolution land-cover map of the Western Guyana Shield (Venezuela) based on remote sensing, and used TEK to validate its relevance for indigenous livelihoods and land uses. We first employed a hyper-temporal remotely sensed vegetation index to derive a land classification system. During a 1300 km, eight day fluvial expedition in roadless areas in the Amazonas State (Venezuela), we visited six indigenous communities who provided geo-referenced data on hunting, fishing and farming activities. We overlaid these TEK data onto the land classification map, to link land classes with indigenous use. We characterized land classes using patterns of greenness temporal change and topo-hydrological information, and proposed 12 land-cover types, grouped into five main landscapes: 1) water bodies; 2) open lands/forest edges; 3) evergreen forests; 4) submontane semideciduous forests, and 5) cloud forests. Each land cover class was identified with a pulsating profile describing temporal changes in greenness, hence we labelled our map as “The Forest Pulse”. These greenness profiles showed a slightly increasing trend, for the period 2000 to 2009, in the land classes representing grassland and scrubland, and a slightly decreasing trend in the classes representing forests. This finding is consistent with a gain in carbon in grassland as a consequence of climate warming, and also with some loss of vegetation in the forests. Thus, our classification shows potential to assess future effects of climate change on landscape. Several classes were significantly connected with agriculture, fishing, overall hunting, and more specifically the hunting of primates, *Mazama americana*, *Dasyprocta fuliginosa*, and *Tayassu pecari*. Our results showed that TEK-based approaches can serve as a basis for validating the livelihood relevance of landscapes in high-value conservation areas, which can form the basis for furthering the management of natural resources in these regions. Rev. Biol. Trop. 64 (4): 1661-1682. Epub 2016 December 01.

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Alarming deforestation rates for the entire Amazon region imperil the future of this high-biodiversity biome (Saatchi, Nelson, Podest, & Holt, 2000). By the end of the 21st century, forest cover in this region is predicted to have declined at rates of up to 80 %, as a result of climate warming and desiccation (Betts, Cox, Collins, Harris, Huntingford, & Jones, 2004; Cox et al., 2004; Intergovernmental Panel on Climate Change, 2007; Salazar, Nobre, & Oyama, 2007; Nepstad, Stickler, Soares-Filho, & Merry, 2008). Range and rates of deforestation in the Amazon have been determined using satellite imagery but mostly at local scales (Asner, Jeller, Pereira, & Zweede, 2002; Marsik, Stevens, & Southworth, 2011). However, effective conservation of Amazonian forest regions requires land cover mapping (Saatchi et al., 2000) to prioritize those expanses in greatest need of protection (Bunce, Barr, Clarke, Howard, & Lane, 1996; Kerr & Ostrovsky, 2003).

Fieldwork by scientists can be severely constrained in regions where personal security may be compromised because of armed conflicts, or geographical remoteness. In these situations, satellite remote sensing is a powerful tool for charting land use patterns and for detecting changes over time (Iverson, Graham, & Cook, 1989; Toivonen, Mäki, & Kalliola, 2007; Baratolo et al., 2011). Even then, adequate ecological interpretation of the resulting land units may be limited by lack of ground data (Stehman & Czaplewski, 1998; Shao & Wu, 2008). To overcome this limitation, local knowledge proffered by indigenous communities living in the area of interest can assist land-cover mapping by identifying landscapes of value to their livelihoods (Berkes, Colding, & Folke, 2000; Herlihy & Knapp, 2003; Robbins, 2003; Naidoo & Hill, 2006; Lauer & Aswani, 2008).

The Venezuelan Amazon, wholly included within the administrative State of Amazonas, is an isolated part of the country that still remains largely uncharted. Although the standing natural vegetation of the region has remained relatively unchanged (Madi, Vázquez, León,

& Rodríguez, 2011), the region's biodiversity is known to be under severe threat (Huber, 2001). The remoteness of the region has indirectly ensured its preservation. However, its inaccessibility has also impeded adequate monitoring of the region's natural richness for its conservation.

New techniques have emerged that utilize local (or traditional) ecological knowledge (hereafter, TEK) to monitor species distributions and population trends over time. These, alongside the use of geospatial technologies, can adequately defeat the constraints of assessing large natural areas such as the Venezuelan Amazonian region (Ostrom, Burger, Field, Norgaard, & Policansky, 1999; Kerr & Ostrovsky, 2003). To date, a number of regional and continental land-cover assessments have been completed for the Amazon Basin (Saatchi et al., 2000; Eva et al., 2004; Gond et al., 2011; Hansen et al., 2013; Mitchard et al., 2014; Pacheco, Aguado, & Mollicone, 2014) that have also included the Venezuelan portion of the Basin. By employing a combination of remote sensing techniques, supported by TEK, we generate a 250 m resolution land-cover classification map for the Venezuelan Amazon. First, we develop a land-cover map from hyper-temporal remotely sensed greenness. Land-cover classes are individually related to pulsating patterns of change in greenness, which help landscape identification and have potential for characterizing the evolution of land classes in future time periods; these profiles form part of the map legend (De Bie et al., 2008), and for this reason we labelled our map as "The Forest Pulse". Onto this map we overlay TEK data provided by six indigenous communities to validate the relevance of our map for indigenous livelihoods and land uses. We then characterize land classes using additional remotely sensed information in order to further understand the correspondence between land classes and landscape units.

MATERIAL AND METHODS

The study area: The study area (0°15'58" - 6°29'20" N & 62°59'35" - 68°7'24" W)

covered a total of 51 000 km² (less than 5 % of the Venezuelan territory) and is underlined by the Guyana Shield (Fig. 1). Due to its high topographic diversity, the state of Amazonas includes parts of the Guyana highlands; a region with high species diversity and endemism (Bates, Hackett, & Cracraft, 1998; Silva, Rylands, & da Fonseca, 2005; López-Osorio & Miranda-Esquivel, 2010). In particular, the Western portion of the Amazonas state contains the world's largest natural waterway (the Casiquiare Canal) that links the Orinoco and the Amazon Rivers. This waterway is a significant natural corridor for gene flow and dispersal of species between the two major river basins (Winemiller, López-Fernández, Taphorn, Nico, & Duque, 2008; Willis et al., 2010).

The area is divisible into: 1) “highlands” along the Western border of the Amazonas State and upper courses of the Ventuari and

Orinoco Rivers (mountain landscapes covered by evergreen forests and scattered with table-top mountains, *tepuis*), and 2) “lowlands”, penepains and low hills along the Casiquiare Canal and the Guainía-Río Negro, Ventuari and Orinoco Rivers (covered by evergreen forests, grassland and scrubland) (Schargel, 2011).

Initial data management: A conceptual diagram summarizing the methodological procedure used in this study is shown in Fig. 2. We used NDVI calculations from 16 day composites of MODIS Gridded Vegetation Indices (product MOD 13) at a 250 m spatial resolution. A set of 216 images corresponding to the period from February 2000 to February 2009 was used (Fig. 3a). These images were collected by the MODIS (Moderate Resolution Imaging Spectroradiometer) sensor onboard the Terra (EOS AM) satellite.

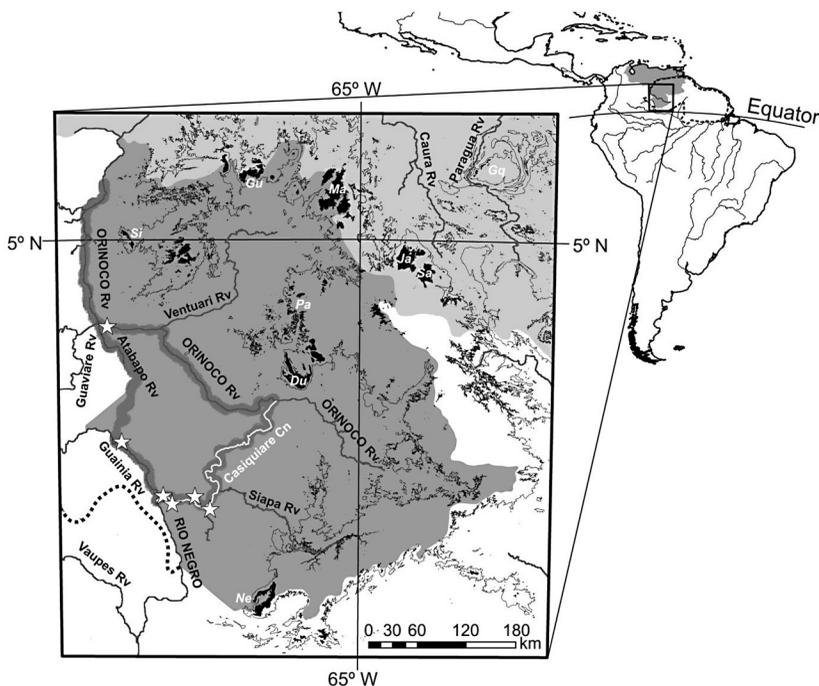


Fig. 1. Study area. The Guyana Shield is delimited by a dashed line and Venezuela is shaded in grey (darker grey represents the Amazonas State within the large rectangle). Wide dark-grey line: route of the expedition; narrow dark grey lines: rivers; white line: Casiquiare Canal; narrow black lines: 500 m altitudinal limit; black polygons: areas with altitudes higher than 1500 m. River names are written in black and tepuis are indicated with white abbreviations (Si: Sipapo; Gu: Guaviare Mountains; Ma: Maigualida; Gq: Guaquinima; Ja: Jaua; Sa: Sarisaniñama; Pa: Paru; Du: Duida; Ne: Neblina). The six indigenous communities visited are identified by stars: 1 = Cascaradura; 2 = Guzmán Blanco; 3 = Chapazón; 4 = Solano; 5 = Kurimakare; 6 = Niñal.

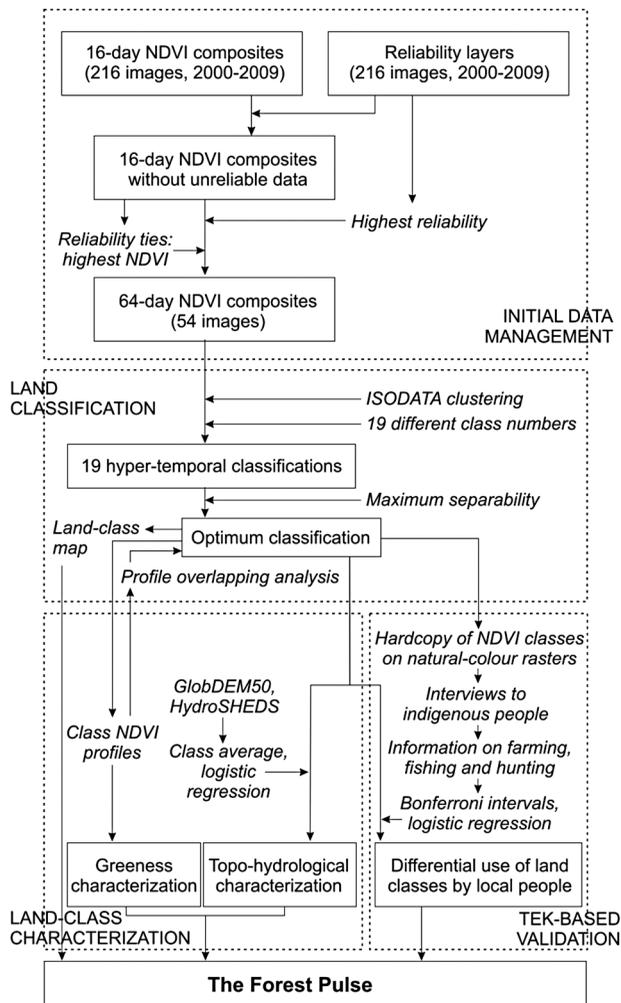


Fig. 2. Conceptual map outlining methodological steps.

In order to compensate for the negative effect of cloud cover on the quality of the NDVI layers, we combined these layers in bi-monthly periods while maximizing confidence with the support of cell “reliability” layers provided by MODIS. Values in reliability layers range from 0 –i.e. good reliable data– to 3 –i.e. covered with clouds (Solano, Didan, Jacobson, & Huete, 2010) (Fig. 3b). Following this, we undertook two main procedures for layer combination: in every cell, we (1) rejected all NDVI values with quality tag >1; (2) selected NDVI values with the lowest tag. In case of

different NDVI values with the same quality tag, we chose the highest value.

Land classification: We used the “separability” classification approach (De Bie, Khan, Toxopeus, Venus, & Skidmore, 2008) (Fig. 2). The ISODATA clustering algorithm (Erdas-Imagine software package) was run to set 19 different hypertemporal land classifications, each containing a different number of classes: 10, 20, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 40, 50 and 60. For every classification, the software produced two separability

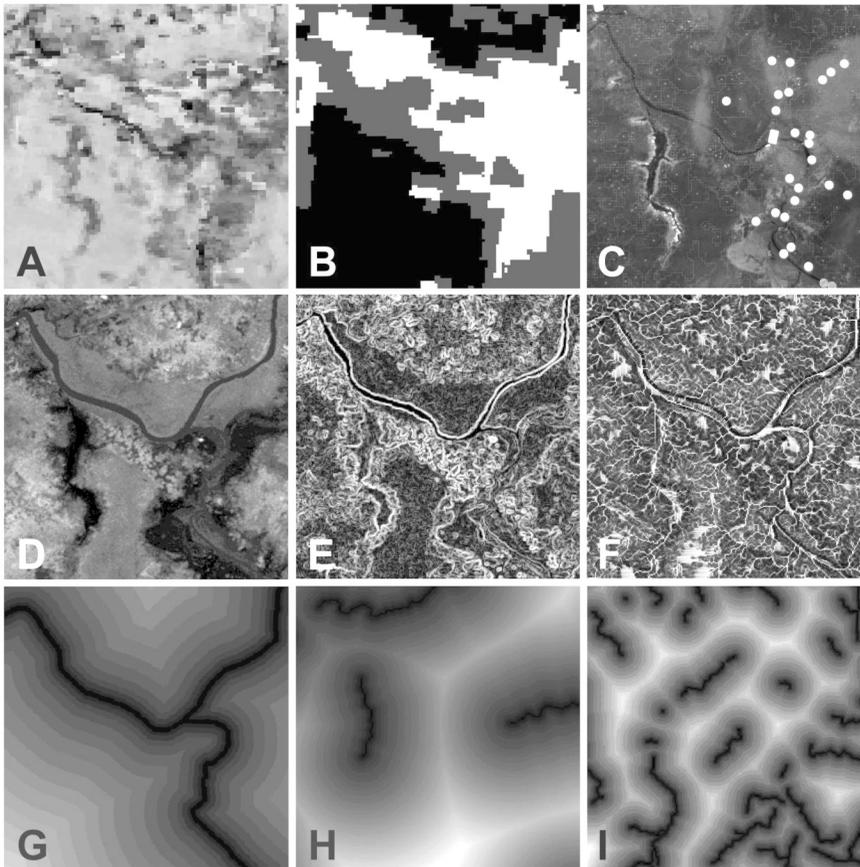


Fig. 3. A sample square showing the variables used for both land classification and class characterization. **A)** 16 day composite of MODIS NDVI of the first half of April 2000; **B)** Reliability of the NDVI value for the same date (white represents pixels covered with clouds whereas black represents reliable data); **C)** Natural-colour-composite raster derived from ETM+ marked with stickers containing information from the indigenous people; **D)** Elevation (SRTM); **E)** Slope; **F)** Compound topographic wetness index (CTI); **G)** Distance from water bodies; **H)** Distance from minor rivers; **I)** Distance from non-perennial streams. Except for **B**, the values of all the variables shown by grey dashes increase with lightness.

values measuring minimum and average divergence between classes. We selected the classification showing the highest separability values. Finally, land classes appearing only in marginal pixels were removed.

Land-class characterization based on greenness: Average NDVI values recorded in the cells of each land class were plotted as NDVI profiles, representing pulsating patterns of changes in greenness. NDVI profile comparisons can be used to determine the type of vegetation cover in the landscapes represented by each class (Arroyo-Mora et al., 2005), since

the NDVI is an indicator of photosynthetically active biomass (Sellers, 1985; Khan, de Bie, van Keulen, Smaling, & Real, 2010) and NDVI temporal dynamics can reflect woodiness, seasonality and leaf type (DeFries et al., 1995). Arroyo-Mora et al. (2005) proposed a relationship between NDVI ranges and forested successional stages, which provides a basis for a preliminary interpretation of our 15 land classes. These authors interpreted NDVI values below 0.45 as pastures; values ranging from 0.45 to 0.58 as sparse patches of woody vegetation, shrubs, and pastures; from 0.58 to 0.70 as intermediate forest successional stages;

from 0.70 to 0.83 as evergreen mature forests. These ranges were conceived for the analysis of dry forests, whereas lowland humid forests prevail in the Guyana Shield (Eva et al., 2004). Thus, the cited correspondences between NDVI and forest stages could be slightly undervalued when applied to humid forests, but they can be still used as a reference.

Serious constraints to the use of the NDVI in late successional stages of tropical forest have been described, because the spectral reflectance of dense forests reaches saturation in the red and near-infrared bands (Saatchi et al., 2000; Arroyo-Mora et al., 2005; Freitas, Mello, & Cruz, 2005). In spite of this, we distinguished different types of dense forests, arising from peculiarities in the respective seasonal oscillation profiles. Temporal dynamics of the NDVI influence woodiness, phenology, leaf type, plant longevity, and other vegetation properties controlling fluxes of water, energy and CO₂ through ecosystems (DeFries et al., 1995). Topo-hydrographic characterizations allowed us to refine land-cover differentiations within the saturation range of NDVI.

Although some overlap between NDVI profiles can remain after the optimum classification was chosen, land classes were combined when both their profile oscillation pattern and their average NDVI values significantly coincided. This was assessed by using the following four steps: (1) interannual average NDVI values were calculated for every class and bi-monthly period of the year; (2) with these averages, for each pair of classes, coincidence in oscillation patterns was measured using Pearson's correlation coefficient, and coincidence in NDVI values quantified using Euclidean distances; (3) land classes were then arranged in two dendrograms using the average-linkage (UPGMA) classification algorithm, the former built with correlations and the latter built with distances; (4) profile overlapping was considered to be significant when two classes were grouped together in both dendrograms, according to a conservative criterion for class clustering: correlations above the 95th percentile, and Euclidean distances below the 5th percentile.

The statistical significance of resulting homogeneous groups was then assessed using analyses of variance in NDVI between all pairs of classes (variations attributable to inter- and intra-annual differences were controlled).

Topo-hydrological land-class characterization: Elevation, and more specifically the 500 m isoline, distinguishes the two main phytogeographical regions described in the Guyana Shield: "Mountains" and "Peneplains of Casiquare and Upper Orinoco" (Huber & Alarcón, 1988; Berry, Huber, & Holst, 1995; Schargel, 2011). In Amazonia, landscape complexity needs to be characterized by a multiple-factor approach involving slope (Mitsuda & Ito, 2011), riverscape (Toivonen, Mäki, & Kalliola, 2007) and inundation (Sippel, Hamilton, Melack, & Novo, 1998; Hamilton, Kellendorfer, Lehner, & Tobler, 2007). Six topo-hydrologic variables were used for land class characterization: elevation, slope, the hydrologically-based Compound Topographic wetness Index (CTI), and linear distances from water bodies, minor rivers and non-perennial streams (Fig. 3d-i). These were derived from the 90 m Digital Elevation Database v4.1, based on raw data from the Shuttle Radar Topography Mission (SRTM) (Jarvis, Reuter, Nelson & Guevara, 2008).

Slope was calculated from elevation using the spatial analyst toolbox of ESRI ArcMap software v10.0. We used the CTI as a proxy of susceptibility to periodical flooding. The CTI is a function of both slope and upstream contributing area per unit width, and estimates soil water content and surface saturation zones (Moore, Grayson & Ladson, 1991):

$$CTI = \ln[(FA + 1) \times CA / \tan B] \quad (1)$$

where *FA* is the water Flow Accumulation –i.e., the amount of upstream area draining water into each cell–, *CA* is the Cell surface Area, and *B* is the slope in radians (Speight, 1980). *B* and *FA* were taken from the hydrologically conditioned digital elevation model distributed with HydroSHEDS (United States Geological Survey-Science for a Changing World, n.d.).

We used *FA* to distinguish between different river types. Cells with *FA* > 1 000 000 were considered to be water bodies, such as the banks of the Orinoco and Negro Rivers, the Southern reach of the Casiquiare canal, and the lower reaches of some tributaries of the Orinoco including the Ventuari, Atabapo, Caura and Paragua Rivers. Cells with *FA* = 10000 to 1 000 000 were classified as minor rivers, and cells with *FA* = 0.1 to 10000 were considered non-perennial streams. Compared to the DNNET coverage of the Digital Chart of the World (Digital Chart of the World data description, n.d.), water bodies and minor rivers approximately matched “inland water body shorelines” and “perennial streams and rivers”, respectively. Euclidean distances to each river type were computed using the “spatial analyst” toolbox of ESRI ArcMap v10.0.

Average values and standard deviations of the topo-hydrologic variables were calculated for every land class, taking into account all cells in the study area. Additionally, we tested whether topo-hydrology can define the probability of cells belonging to a given class. For this, we randomly selected 60 000 cells throughout the study area; we then performed a forward-backward stepwise logistic regression per class, using the correspondence of each cell with the class (1/0) as response variable, and the topo-hydrologic variable values in each cell as explanatory factors. Wald’s statistic was used to estimate the relative importance of variables selected for entering in logistic equations.

TEK-based validation of land-classes, according to differential use by local people:

During a 1 300 km, eight day fluvial expedition in roadless areas of the Amazonas state (Venezuela) (Fig. 1), we visited six indigenous communities. Because our expedition was prohibited from moving freely within the study area for security reasons, we were unable to carry out any field work in areas more than 100 m from the main rivers. Despite this, we were officially authorized, controlled and eventually assisted by the army to complete the planned itinerary, and made

contact with six remote indigenous settlements –Casaradura (04°00’25” N, 67°39’40” W), Niñal (01°54’50” N, 60°36’00” W), Kurimakare (02°01’10” N, 66°44’15” W), Chapazón (02°01’20” N, 67°05’04” W), Solano (02°00’00” N, 66°57’05” W) and Guzmán Blanco (02°40’10” N, 67°30’30” W)– of five different ethnic origins (Baniva, Bare, Kurripaco, Warekena and Yeral).

The collaboration between the indigenous and scientific parties was formalized following all the legal and cultural requirements. In Spain, the project was evaluated and approved by AECID –which is part of the Spanish Ministry of Foreign Affairs– and by the Vice-Rectorate of International Relationships of the University of Malaga (UMA). In Venezuela, the project had the explicit endorsement of the Universidad Central de Venezuela and of the Universidad Pedagógica Experimental Libertador (UPEL), and had the institutional support of the Venezuelan Ministry of Education. Two delegates of the Venezuelan Ministry of Education in Puerto Ayacucho (Estado Amazonas), namely Antonio Largo and Luis Yakamé, joined the expedition with instructions for introducing the scientific team and the project to the indigenous communities. In accordance with the customs of the local participants, in each community indigenous members would celebrate a meeting to discuss our request for them to participate in our research, in their own languages. Finally, their collaboration in the project was officially announced by the community leader (“el capitán”). We then accepted the commitment to admit the indigenous communities as co-authors of the products derived from their participation. This agreement was verbal, but all individual participants provided written personal identification (including name, identification card number and signature). We then presented to a group of community members (Appendix 1) hardcopy remote sensing images (28.5 m resolution; 1:75 000 scale) that approximately covered a 4500 km² surface area around their settlements. These images contained polygons outlining our land classification on a natural-colour-composite raster

generated from Landsat 7 ETM+ data (Fig. 3c). Indigenous participants were asked to point on the Landsat image, as accurately as possible, to the sites in which farming, fishing and hunting were usually undertaken. They were also asked to specify which species were hunted in each hunting site. So as not to influence responses with leading questions, the participants were given total freedom to locate sites and their uses, i.e. we gave no information that could associate land classes with specific landscape units. With only a few exceptions, participants were able in orienting and interpreting the maps. Participants identified sites and their corresponding uses by stickers markers onto the images presented to them (Fig. 3c).

We validated the significance of our land-cover classification for local people by testing for non-random spatial relationships between land classes and livelihood activities declared by participating community members. We used two approaches for the analysis of TEK data. Firstly, we determined whether specific land classes were selected for particular uses. With this aim, we used Bonferroni confidence intervals (with Z-critical values = 1.96, d.f. = 2, $P = 0.05$; see Byers, Steinhorst & Krausman, 1984; Steinheim, Wegge, Fjellstad, Jnawali, & Weladji, 2005) to compare observed and expected frequencies with which every use was related to every class (expected frequency was estimated according to each land class prevalence in the study area). Secondly, we assessed the correspondence between uses and land classes using logistic regressions. Both response and explanatory variables were binary (1/0), and described the presence/absence of a given use in a site and the correspondence between this site and a given land class, respectively.

RESULTS

Land classification: We chose 30 classes, in which the highest value for average separability coincided with intermediate values of minimum separability (Fig. S1 in Supplementary Material 1). Ten classes were later discarded because they only appeared in marginal

cells, accounting for only 0.0071 % of the study area. The option showing the highest value for minimum separability (within 26 classes) was rejected because it also showed the lowest value for average separability.

Extensive overlap between classes was detected where $NDVI > 0.8$ (Fig. S2a in Supplementary Material 1). A set of 15 classes resulted from the combination of classes with highly coincident NDVI values and greenness oscillation profiles (Fig. S2b and Fig. 4).

Land-class characterization based on greenness: Class 1 showed $NDVI < 0.2$; classes 2, 3 and 5, with $NDVI = 0.3$ to 0.7 , had greenness profiles with a seasonal decrease in March-April and a quick rise in May-June; classes 9, 11, 13, 14 and 15 had $NDVI > 0.8$, and showed a slight decrease in May-June followed by a 2 months lasting recovering; class 15 had the most stable profile, at around $NDVI = 0.9$; class 7 showed transitional NDVI values and profile between classes 5 and 11; classes 10 and 12, whose NDVI values widely overlapped with those of classes 9, 11, 13 and 14, had, in contrast, oscillation profiles alternating two yearly decreases (May-June, November-December) with two peaks (January-February, July-August); classes 4, 6 and 8 showed the most pronounced NDVI oscillations, class 4 having a similar pattern to that of classes 10 and 12, whereas classes 6 and 8 had a yearly peak in January-February and a long-lasting bottom between May and August.

Topo-hydrological land-class characterization: In our land classification, elevation was the main factor conditioning the frequency of land-class dominance (compare Figs. 1 and 4). When NDVI classes were arranged along topo-hydrological gradients (Fig. S3 in Supplementary Material 1), they showed exponential relationships with elevation (determination coefficient, $R^2 = 0.95$), slope ($R^2 = 0.95$) and susceptibility to flooding (CTI) ($R^2 = 0.98$), meaning gradually increasing trends. Instead, classes showed 3rd-order polynomial trends regarding distances to water bodies ($R^2 = 0.99$),

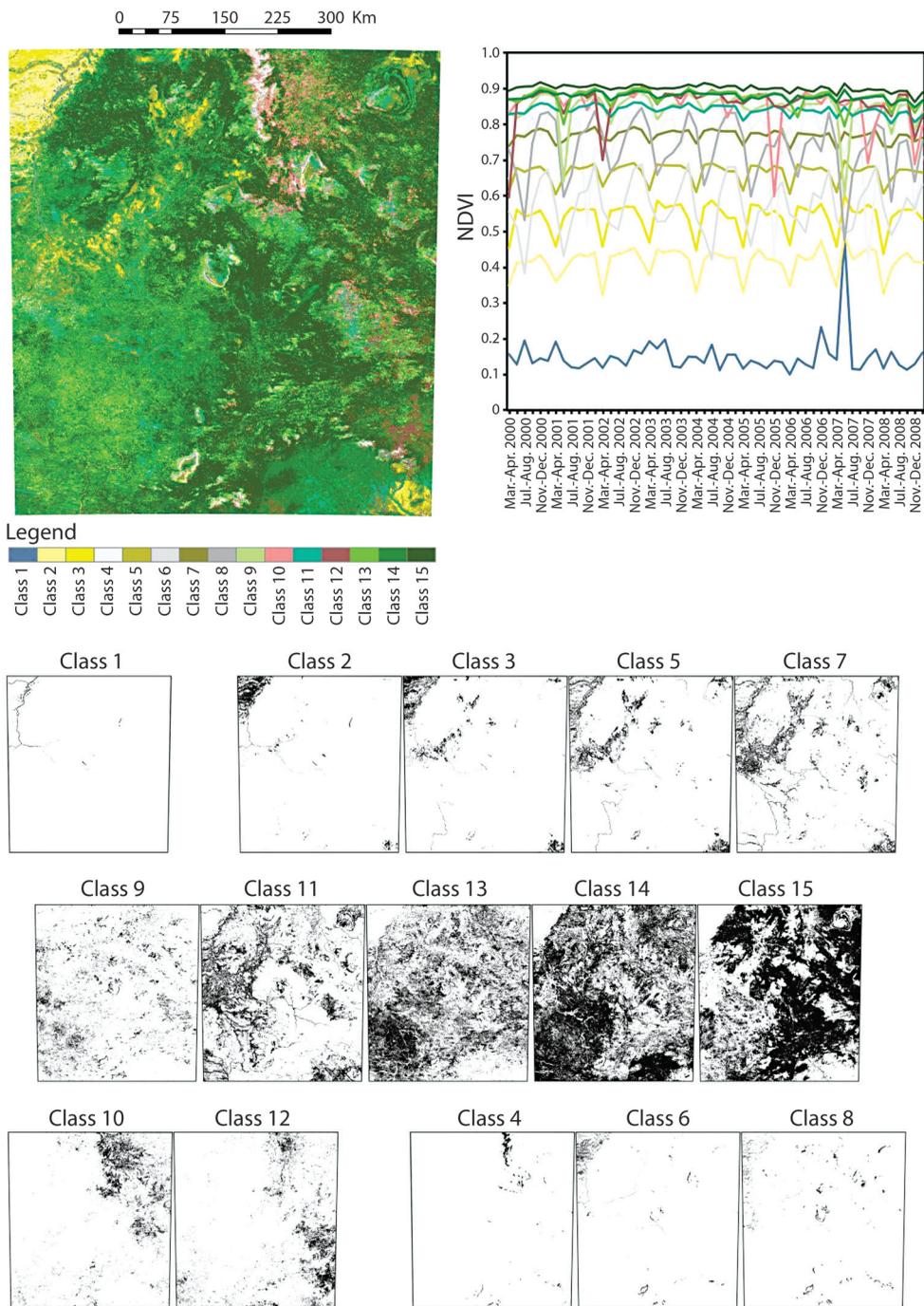


Fig. 4. Preliminary land classification of the western Guyana Shield into 15 classes. Greenness profiles identified using the average NDVI are plotted for every class. A spatial disaggregation of the 15 classes is shown.

to minor rivers ($R^2 = 0.99$) and to non-perennial streams ($R^2 = 0.98$); this points to differences between classes when these are either in the close vicinity or very far from water streams.

Closeness to water bodies was the most important topo-hydrological feature explaining the presence of classes 1, 2, 3, 5 and 7 (Table 1). Class 1 is at low average elevation (< 200 m), and is the most susceptible class to flooding (i.e. with highest CTI) and the closest one to water bodies (Fig. S3). Also at low altitudes (< 200 m) and moderate slopes (< 5°), there are classes 2 and 3 (Fig. S3, Table 1), the latter being highly susceptible to flooding (CTI > 14). Both are usually found surrounding land class 1 (Fig. 5). Classes 5 and 7 are also prone-to-flooding areas located at gentle slopes, and are in the neighbourhoods of minor rivers and non-perennial streams. In contrast, the highest

average elevations (> 1 000 m), slopes (> 15°) and distances from rivers, and the lowest flood risk (average CTI around 12) is shown by classes 4 and 8, closely followed by class 6 (Fig. S3, Table 1).

Land types with the highest level of greenness (NDVI > 0.8) are arranged along the middle stretch of the gradient defined by elevation, slope and susceptibility to flooding (Fig. S3). Nevertheless, topography and hydrography still permitted differentiation between classes even though the NDVI could show saturation at these values (Fig. S3, Table 1). Classes 9, 10 and 12 occupy rarely flooded highlands (in average, CTI < 14, elevation > 400 m, slope > 5°); class 12 is, however, farther from water bodies than the other two. In contrast, classes 11 and 14 are found mostly in lowly sloped (< 5°) lands; class 11 is more floodable (CTI >

TABLE 1
Logistic regressions of the 15 land classes initially identified in the western Guyana Shield (see Fig. 4) on six topo-hydrological variables

| Class | 1 | | | | | | 2 | | | | | | 3 | | | | | |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|----|--|
| V ¹ | WB | CTI | S | | | | WB | E | NPS | CTI | S | WB | E | CTI | S | MR | | |
| S ² | - | + | + | | | | - | - | + | + | - | - | - | + | - | + | | |
| W ³ | 113 | 55 | 34 | | | | 199 | 152 | 66 | 14 | 5.2 | 113 | 86 | 62 | 60 | 34 | | |
| Class | 4 | | | | | 5 | | | | | 6 | | | | | | | |
| V ¹ | E | S | MR | WB | | WB | CTI | S | E | MR | NPS | E | WB | CTI | S | MR | | |
| S ² | + | + | + | - | | - | + | - | + | - | - | + | - | + | + | + | | |
| W ³ | 315 | 74 | 38 | 5.6 | | 165 | 109 | 49 | 40 | 25 | 4.9 | 142 | 124 | 36 | 26 | 14 | | |
| Class | 7 | | | | | | 8 | | | | | | 9 | | | | | |
| V ¹ | WB | E | CTI | MR | NPS | S | E | S | WB | NPS | MR | CTI | E | MR | WB | NPS | S | |
| S ² | - | + | + | - | - | - | + | + | - | + | + | + | + | + | - | + | + | |
| W ³ | 378 | 150 | 111 | 62 | 21 | 6.8 | 375 | 99 | 76 | 75 | 20 | 5.7 | 160 | 85 | 72 | 13 | 11 | |
| Class | 10 | | | | 11 | | | | | 12 | | | | | | | | |
| V ¹ | E | WB | CTI | MR | E | CTI | MR | WB | S | WB | E | MR | CTI | | | | | |
| S ² | + | - | - | + | + | + | - | - | - | + | + | + | - | | | | | |
| W ³ | 700 | 39 | 18 | 7.4 | 147 | 117 | 82 | 66 | 34 | 55 | 41 | 37 | 11 | | | | | |
| Class | 13 | | | | | 14 | | | | | 15 | | | | | | | |
| V ¹ | MR | WB | E | S | NPS | E | WB | S | MR | NPS | CTI | MR | S | WB | E | NPS | | |
| S ² | + | - | + | - | + | - | + | - | + | + | - | - | + | + | - | - | | |
| W ³ | 147 | 99 | 41 | 20 | 14 | 809 | 509 | 290 | 94 | 18 | 595 | 392 | 378 | 274 | 122 | 120 | | |

1. V = variable — Elevation (E), Slope (S), Compound Topographic index (CTI), distance from Water Bodies (WB), distance from Minor Rivers (MR), distance from Non-Perennial Streams (NPS).
2. S = sign (+/-) of the variable coefficient in the logistic equation.
3. W = Wald statistic indicating the variable contribution in the regression. All variables had significant W with $P < 0.05$. Based on 60,000 randomly selected points.



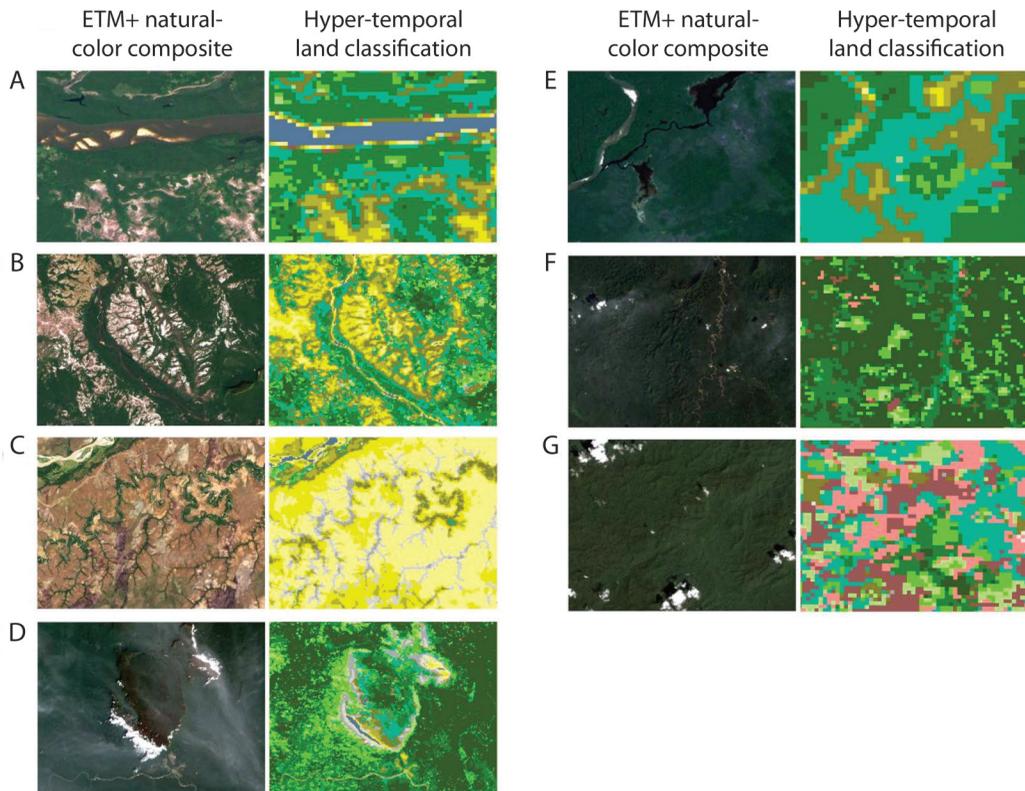


Fig. 5. Sample of some characteristic patterns. Images represent natural-colour-composite raster images generated from Landsat 7 ETM+ data (left) and the hyper-temporal land classification shown in Figure 4 (right). a) Water bodies in the Orinoco River. **b)** Gradient in open vegetation cover from bareland/grassland to forest edges next to the convergence of the Orinoco Ventuari and Guaviare rivers. **c)** Gallery forests along Orinoco tributaries across savannas in the north-west of the study area. **d)** Duida Tepui next to the Orinoco's upper course. **e)** Seasonally flooded evergreen forests around the Casiquiare Canal. **f)** Patterns of *terra firme* evergreen forest in the highlands. **g)** Semideciduous forests in the eastern borders between Venezuela and Brazil. Class colours as in Fig. 4.

14) and closer to rivers than class 14, whereas this one lays at lower altitudes than class 11. In the middle of the elevation gradient, there are classes 13 and 15, the latter being farther from water bodies but closer to minor rivers and streams. Classes 9, 13, 14 and 15 are often in the neighbourhood of each other, and are frequently limiting with class 11 (Fig. 5).

Cloudiness correction and final land-cover classification: Despite the negative effect of cloud cover on the quality of the NDVI layers was compensated with the support of information on cell reliability, some parts of the study area still showed weaknesses in some

classes resulting from occasional or persistent cloudiness (Fig. S4 in Supplementary Material Fig. 1). This affected to some cells included in classes 1, 4, 6, 9, 10, 12 and 13, and justified class-merging decisions driving to a final number of twelve landscape types identified.

Extremely persistent cloudiness led to weaknesses in correctly identifying class 1 in some cells that were always surrounded by class 2. This happened on the Duida and Jaua tepuis, as a result of unreliably low NDVI values (Fig. S4a), and in some “lagoon-like” patches, showing persistent cloudiness between March and October, in the north-west, around the Orinoco River (Fig. S4b). These cells

were reclassified in class 2. Also across the savannas on the North-West, small tributaries of the Orinoco River were frequently outlined by classes 6 and 8 (Fig. 5c). However, Landsat ETM+ images for these areas hardly differ from those in classes 5 and 7. Every year, non-reliable NDVI values were identified there mainly in May-June (the start of the rainy season), on cells belonging to classes 6 and 8, but rarely in cells of classes 5 and 7. So, classes 6 and 8 occurring in the plain savannas of the North-West were merged with classes 5 and 7, respectively.

In the forest areas, classes 9 and 13 were visually recognized as patterns of occasional cloudiness. Both classes were mutually associated at high frequency, and always surrounded by class 14. Their NDVI profiles overlapped with that of class 14, except for two sudden decreases in June-August in both 2001 and 2007 (Fig. 4). Precisely during these months, there is a high apparent correspondence between

cloudiness and these classes (Fig. S4c). So, classes 9 and 13 were merged with class 14. On the other hand, the NDVI profile of class 10 strongly overlapped with that of class 12, except for three sharp decreases detected in November-December of 2005, 2007 and 2008. These drops coincided with highly apparent cloud patterns that are easily recognizable, precisely in those dates, on class 10 (Fig. S4d). We thus merged class 10 with class 12.

Finally, twelve landscape types (Fig. 6), grouped into five main landscapes, were identified after greenness and topo-hydrographical characterization: 1) Class 1 (water bodies); 2) classes 2, 3, 5 and 7 (open lands and forest edges, including grasslands and bare lands, as well as open scrublands); 3) classes 11, 14 and 15 (evergreen forests, including floodable scrublands with spare trees/narrow gallery forests, floodable evergreen forest edges/gallery forests, seasonally flooded evergreen forests, lowland evergreen forests on *terra firme*, and

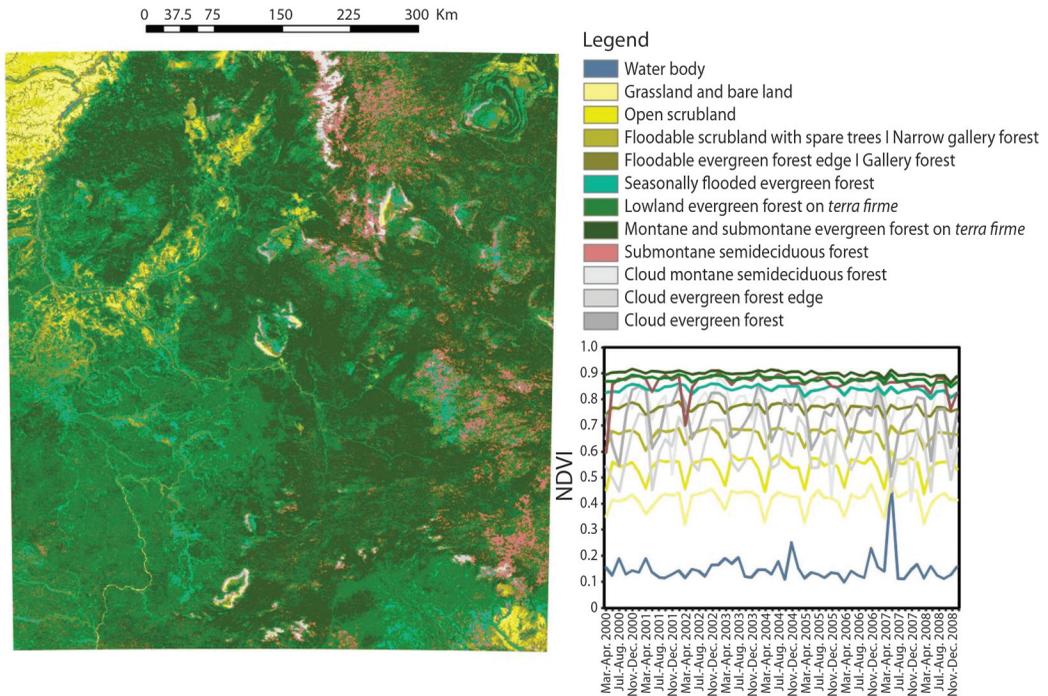


Fig. 6. “The Forest Pulse”. Final land classification of the western Guyana Shield into 12 landscape types after a 15 class greenness-based classification (see Fig. 4) was assessed using topo-hydrographical data. Greenness profiles as identified using the NDVI are plotted for every type of landscape (bottom right).

montane and submontane evergreen forests on *terra firme*); 4) class 12 (submontane semi-deciduous forests); and 5) classes 4, 6 and 8 (cloud forest, including cloud montane semi-deciduous forests, cloud evergreen forest edges, and cloud evergreen forests). The identification of these landscapes is discussed below.

TEK-based validation of land-classes, according to differential use by local people: Traditional ecological knowledge (TEK) obtained from the participating communities highlighted a meaningful relationship between livelihood activities and landscapes. Interviewed community members affirmed that farming sites –“conucos”– were always cleared on *terra firme*, where flooding is not a risk to crops. Waters near river banks and within flooded forest were preferred to open waters for fishing; and in flooded forests, arboreal animals like birds and primates were more hunt-able from boats, usually shot with guns and blowpipes. The analyses validated statistically

the existence of different preferences expressed by the interviewees in the use made of different land classes (Table 2 and Table 3): lowland evergreen forests in *terra firme* were significantly preferred for agriculture, which was an unlikely activity in seasonally flooded evergreen forests; flooded forest were positively, and lowland evergreen forests negatively chosen for fishing and hunting (compared to the availability of these classes in the study area); and submontane deciduous forests were positively selected for hunting.

Indigenous people identified areas that were used for hunting particular animal groups (Table 2 and Table 3). Thus, seasonally flooded evergreen forests were positively selected for hunting primates; this class also recorded the highest bird catches (“pajui”, black curassow, *Crax alector*; “pava”, blue-throated piping-guan, *Pipile cumanensis* and spix’s guan, *Penelope jacquacu*; family Cracidae), but this prevalence was not statistically significant. For ungulates (Order Cetartiodactyla), informants

TABLE 2
Differential use of landscape types by indigenous people (see Fig. 6)

| Landscape type ¹ | EF ² | OO ³ | OF ⁴ | LL ^{5,7} | UL ^{6,7} | S ⁸ |
|--|-----------------|-----------------|-----------------|-------------------|-------------------|----------------|
| Agriculture | | | | | | |
| Lowland EGF ⁹ on <i>terra firme</i> | 0.5 | 12 | 0.8 | 0.598 | 1.002 | + |
| Fishing | | | | | | |
| Seasonally flooded EGF ⁹ | 0.3 | 10 | 0.526 | 0.302 | 0.751 | + |
| Lowland EGF ⁹ on <i>terra firme</i> | 0.5 | 5 | 0.263 | 0.065 | 0.461 | - |
| Hunting | | | | | | |
| Seasonally flooded EGF ⁹ | 0.3 | 46 | 0.426 | 0.333 | 0.519 | + |
| Submontane deciduous forest | 0.006 | 6 | 0.055 | 0.012 | 0.099 | + |
| Lowland EGF ⁹ on <i>terra firme</i> | 0.5 | 42 | 0.389 | 0.297 | 0.481 | - |
| Hunting primates | | | | | | |
| Seasonally flooded EGF ⁹ | 0.3 | 4 | 0.8 | 0.449 | 1.151 | + |

1. Only classes significantly selected ($P < 0.05$) are shown.
2. EF = expected frequency of every class.
3. OO = number of observed occurrences of each use in every class.
4. OF = observed frequency of every class.
5. LL = lower limit of the Bonferroni confidence interval.
6. UL = upper limit of the Bonferroni confidence interval.
7. Computed from OF with Z-critical values = 1.96, d.f. = 2, $P = 0.05$.
8. S = significant positive or negative selection observed. The selection was positive if EF was lower than LL and negative if EF was higher than UL.
9. EGF = Evergreen forest.

According to the method of Byers, Steinhorst & Krausman (1984).

TABLE 3

Significant logistic regressions of 5 landscape types identified in the western Guyana Shield (see Fig. 6) on variables representing land uses and/or hunted animal species by indigenous people

| Landscape type | Floodable EGF ¹ edge / Gallery forest | Seasonally flooded EGF ¹ | Submontane deciduous forest |
|-----------------|--|---|-----------------------------|
| LU ² | RBD | A | BA |
| S ³ | + | - | + |
| W ⁴ | 3.3 | 4.8 | 5.4 |
| Landscape type | Lowland EGF ¹ on <i>terra firme</i> | Montane and submontane EGF ¹ on <i>terra firme</i> | |
| LU ² | A | GM | WLP |
| S ³ | + | + | + |
| W ⁴ | 12.6 | 4.9 | 6.8 |

1. EGF = Evergreen forest.
2. LU = land use – Agriculture (A); hunting of red brocket deer (RBD), black agouti (BA), white-lipped peccary (WLP) and ground mammals (GM).
3. S = sign (+/-) of variable coefficients in logistic equations.
4. W = Wald statistic indicating the variable contribution in the regression. All variables had significant W with $P < 0.05$.

reported specific hunting sites for the red brocket deer (“venado”, *Mazama americana*, family Cervidae) and white-lipped peccary (“báquiro”, *Tayassu pecari*, family Tayasuidae). Specific localities were also identified for hunting of the Brazilian tapir (“danto”, *Tapirus terrestris*, family Tapiridae, Order Perissodactyla). Among the order Rodentia, two species were mentioned: black agouty (“picures”, *Dasyprocta fuliginosa*, family Dasyproctidae) and paca (“lapa”, *Cuniculus paca*, family Cuniculidae). The analyses validated the consideration of floodable evergreen forest edges and gallery forests as a favourable landscape for hunting red brocket deer; of submontane deciduous forest for hunting black agouti; of lowland evergreen forests in *terra firme* for hunting ground mammals in general –i.e. the five above-mentioned species together–; and of montane and submontane evergreen forests on *terra firme* for hunting white-lipped peccary (Table 3).

DISCUSSION

In this paper, we developed a land-cover map from hyper-temporal remotely sensed greenness, whose value to the indigenous livelihoods in the Western Guyana Shield has been demonstrated through TEK. Considering TEK

allowed us to get a better understanding of how indigenous groups use different habitats, as well as of the habitats that are favourable for key species that are important for indigenous peoples. However, the most important TEK contribution here was the validation of the significance of our land-cover classification for the indigenous groups. This demonstrates that the human use of land can be detected even in wild landscapes, which indicates that indigenous people make a logical management of their environment according to their needs and to the land characteristics. The information provided by the local participants involved different aspects of their use of environment, mostly focused on farming, fishing and hunting; further insights on the significance of our land classes could be achieved in the future by analysing differential uses regarding plant gathering with food and medicinal purposes. Above all, our study is a public recognition of how TEK can serve to provide purely scientific outputs with social meaningfulness. TEK is increasingly accepted by scientists as an adequate means for understanding the natural world (Herlihy & Knapp, 2003), already used in a number of studies to support the development and supervision of land-cover maps based on remote sensing (Robbins, 2003; Lauer &

Aswani, 2008). Traditional practices are now considered forms of ecosystem management as well (Omotayo & Musa, 1999; Berkes, Colding, & Folke, 2000). In our work in particular, we argue that the level of collaboration between us was such that shared authorship was a fair acknowledgement of contribution and deep commitment of the Amazonian communities to the goals of the research presented in this paper.

The land-class characterization performed by using temporal patterns of greenness and topo-hydrology allows us to propose hypotheses about landscape units described by the land-cover classes. However, it is not possible to assess the accuracy of landscape identification without ground or remote-sensing data as reference points to supervision. For example, major Amazonian landscapes (e.g. flooded and semideciduous forests) are characterized by seasonal variations that are not visible in satellite images with natural-colour such as Landsat 7 ETM+. Nevertheless, although accuracy assessment should be undertaken in the future, given the available information obtained in our study we are proposing five main landscape types for the Western Guyana Shield: water bodies, open lands (i.e. bare lands, grasslands) and forest edges, evergreen forests, semideciduous forests, and cloud forests. As outlined hereafter, the information provided by TEK showed a strong congruence between land classes and our interpretation of the different landscapes.

Water bodies are proposed to correspond with class 1, which shows the lowest NDVI values were shown by class 1. This is so because water has extremely low reflectance in the red and the near infra-red spectral bands (Pope & Fry, 1997). The topo-hydrological characterization of this class also indicated the highest potential for receiving huge amounts of water flow (CTI). This class appeared in main water courses (around 750 m wide channels in the Orinoco and the mouth of the Guaviare River), where water was never combined with mainland. Cells containing water and riversides were represented, instead, by other classes (see below).

We propose a correspondence between open lands and forest edges with classes 2, 3, 5 and 7. According to greenness (Arroyo-Mora et al., 2005), class 2 should be identified as pasture areas, and classes 3, 5 and 7, respectively, as early, intermediate and late forest successional stages. These classes seem to represent a gradient in open vegetation cover from bare land/grassland to forest, located in lowlands and in the neighbourhood of river courses. The oscillation patterns of the NDVI in these four classes show a steep decrease of greenness at the end of the dry season (March-April) and a rapid increase after the first rains (May-June), which is consistent with the expected phenology of a grass cover that, after withering, sprouts as soon as water falls on it again. Grasslands must thus have a strong presence even in classes 5 and 7. Classes 2, 3, 5 and 7 are generally shaped in a spatial pattern where core class 2 patches are integrated within a matrix of class 3 which, in turn, is surrounded by class 5. The edge of this complex area is, most of the times, composed of thin class 7 surfaces, which normally border class 11. Such a pattern is closely reproduced on tepui tops.

Classes 2 and 3 seem to correspond to grasslands including flood-prone areas. The low greenness of class 2 suggests predominance of herbaceous plants and bare lands –rocky outcrops; river bars–, whereas class 3 could include more stable vegetation, such as scrubs and isolated trees combined with grass. Different authors (Hansen, DeFries, Townshend, & Sohlberg, 2000; Eva et al., 2004; Freitas, Mello, & Cruz, 2005; Bontemps, Pierre, & van Bogaert, 2010; Huber & Oliveira-Miranda, 2010) have identified mostly savannas, grasslands and open scrublands in the areas where classes 2 and 3 predominate.

Classes 5 and 7 are greener than classes 2 and 3, highly prone to flooding, and associated with minor water courses in dendritic formations. Classes 5 and 7 surely represent masses of floodable woody vegetation interspersed with grassland patches, often arranged as gallery forests and forest edges. The latter fundamentally involve margins of class 11.

The woody component is forest in class 7, and scrubland in class 5. The identification of class 7 with gallery forests and forest edges is supported by the information provided by TEK, which identified this class as significantly suitable for hunting red brocket deer. This species is typically found in mature and secondary forests, gallery forests, forest borders and savannas near the forest edge (Emmons, 1997); humid forest borders are indeed the main habitat of this species in the Amazon (Bodmer, 1997). The indigenous people of several communities used the word “savanneta” to describe this type of landscape.

In summary, we propose identifying that class 2 areas are grasslands and bare lands –i.e. savannas; class 3 areas are open scrubland; class 5 areas are floodable scrubland with sparse trees– i.e. “savannetas” –and narrow gallery forests; and class 7 areas are floodable evergreen forest edges and gallery forests.

Evergreen forests are proposed to correspond to classes 11, 14 and 15. The most stable profiles were shown by seven classes that had, throughout the year, NDVI values above 0.83, i.e. the maximum value of the range identified by Arroyo-Mora et al. (2005) as mature forest. These classes showed two different types of temporal behaviours: classes 11, 14 and 15 underwent a decreasing trend of greenness reaching a minimum just after the start of the rains (May-June), gradually recovering between two to four months later. Instead, class 12 undergoes two decreases in greenness per year. Leaf mortality in Amazonian evergreen forest is highest at the end of the dry season, and leaf biomass takes some months to recover completely after the arrival of the rains (Malhado, Costa, de Lima, Portilho, & Figueiredo, 2009), which is consistent with the former of these two types of profiles. We thus identify classes 11, 14 and 15 with evergreen forests, of which three subtypes are distinguished: flooded evergreen forests, evergreen forests on *terra firme*, and montane and submontane evergreen forests on *terra firme*.

We suggest that class 11 is identifiable with seasonally flooded evergreen forests.

In the study area, these forests appear mostly in the Western lands around the Casiquiare Canal, coinciding with the areas identified by Huber and Oliveira-Miranda (2010) as riverine bushland and lowland floodable forests. Besides, they appear near to the Guaviare River and on tepui tops. TEK supports the identification of class 11 with floodable forests because this class was significantly selected for fishing and for hunting primates, which is most frequently made from boats in flooded forests. Additionally, class 11 was significantly avoided by farmers for clearing the forest for agriculture.

Evergreen forests on *terra firme*, protected from seasonal floods (Saatchi et al., 2000) and with very steady profiles, clearly corresponded to classes 14 and 15. The fact that class 14 –i.e., the dominant class in the Western lowlands– was positively selected for agriculture, and negatively for fishing, is consistent with its identification as *terra firme* evergreen forests. More strange seems to be the fact that class 14 was negatively selected for hunting, whereas it was significantly suitable for hunting ground-living mammals. Hunting is a frequent activity in class 14; indeed 39 % of the hunting sites recorded are located in this class. Its negative selection indicates, instead, that there is a bias against the use of class 14 for hunting, compared to the availability of this landscape in the study area (> 50 %). The relevance of this result is that more open landscapes are preferred for hunting to closer *terra firme* forests, as is the case of flooded forests (class 11, which recorded 43 % of the hunting sites identified). Furthermore, most elevated and sloping lands in the North and the East are covered by class 15, which were significantly selected by indigenous people for hunting white-lipped peccaries; 60 % of this species’ distribution occupies the interior of humid tropical forests (Emmons, 1997; SOWLS, 1984). We have, thus, distinguished between lowland (class 14) and montane/submontane (class 15) *terra firme* evergreen forests. The very low susceptibility to flooding of class 15 is likely to be the cause of the exceptionally steady behaviour of greenness in these forests.

In summary, we suggest identifying seasonally flooded evergreen forests with class 11; lowland evergreen forests on *terra firme* with class 14; and montane and submontane evergreen forests on *terra firme* with class 15.

Submontane semideciduous forests are proposed to correspond to class 12. As mentioned above, this class shows different NDVI profiles compared with those we identify with evergreen forests. In class 12, greenness decreases at the start of the dry season (May-June), and again before the rains (November-December). In the lands where class 12 appears with highest frequency in our study area, around the Eastern borders between Venezuela and Brazil and in the North-East, Huber & Oliveira-Miranda (2010) described a wide occurrence of semideciduous forests whose dominant trees lose much of their foliage during the dry season. Our proposal is to define class 12 as patches of submontane semideciduous forests that grow within a matrix of evergreen forest. This is consistent with the identification of class 10 by local people as suitable areas for hunting black agouties, as this species is mainly found in mature deciduous and montane forests (Emmons, 1997).

Cloud forests are characterized by the persistence of clouds, just like classes 4, 6 and 8. Out of the North-Western savannas, classes 6 and 8 only appear at high altitudes around tepuis and, in association with class 4, in the highest mountains. The distribution of this association strongly coincides with the distribution of cloud forests in Guyanese tepuis (Ataroff, 2001), at altitudes between 1 500 and 2 000 m and at slopes between 20° and 35°. Mountain areas occupied by classes 6 and 8 frequently showed non-reliable NDVI values, caused by heavy cloud, at the start of the rainy season (May-June). The profiles of these classes appear like much amplified versions of evergreen forest (classes 9, 11, 13, 14 and 15) profiles. Maximum NDVI values of class 8 are within the range shown by evergreen forests; we thus suggest identifying class 8 in the highlands with cloud evergreen forests. Instead, class 6 covers the tops of the rocky, vertical

cliffs of the tepuis, which form elongated transitions between class 3 (open areas) and class 8. Class 6 is more prone to flooding than class 8, and surely represents cloud evergreen forest edges.

In contrast to classes 6 and 8, heavy cloudiness in class 4 caused unreliability of NDVI values in the middle of the dry season (November to February). This class' profile is similar to that of class 10 –which dominates in the surroundings–, but with higher amplitude in oscillations. We, thus, suggest identifying class 4 with cloud semideciduous forests, whose occurrence at altitudes between 800 m and 1 500 m has also been described in the Guyana Shield (Huber, 1995a; 1995b).

One of the main contributions of our land-cover map is that every land class is individually related to a “time-profile-based signature” which forms part of the map legend (see De Bie et al., 2008). The pulsating patterns of hyper-temporal greenness profiles, which have defined every land-cover type, have led to us to label our map as “The Forest Pulse”. The expression “pulse” is taken from physics in the sense of “a burst of some form of energy that is sudden and strong” (Cambridge Dictionaries Online, n.d.). With “pulse”, however, we also want to illustrate the “firm hand” that can be achieved when there is synergy among scientific and traditional ecological knowledge, especially where logistic and natural restrictions impose obstacles for scientific field-work.

In this study, greenness profiles for the period 2000 to 2009 showed a slightly increasing trend in the low-NDVI land classes representing grassland and scrubland, and a slightly decreasing trend in the classes representing forests. This finding is consistent with both a gain in carbon in grassland as a consequence of warming (Phillips et al., 1998), and also with some loss of vegetation in the forests (Cox et al., 2004). Nevertheless, processes other than climate changes could explain this trend; for example, the constant openness of forest areas for agriculture (“conucos”) around the indigenous communities and the growth of secondary forests where farming has been abandoned

(Freire, 2007). Using observed greenness profiles to characterize the evolution of land classes could involve circular reasoning, because the classification of each cell in either one class or another is itself a consequence of the observed hyper-temporal variations of greenness. However, this classification still has the potential to assess the effects of climate change on landscape. Defining future greenness profiles of every type of landscape will enable the analysis of correlations between changes in greenness and deviations in climatic variables.

The significant relationship between land types and hunted species adds a new dimension to the potential of our land-cover map. All the species that were identified by the interviewed people during our surveys are among the ten most important vertebrate species for the survival of the Amazon people (Real, 2009, Real et al., 2009). Thus, future analyses of how climate change or other circumstances could impact the different landscapes can be consistently related to their potential effects on the natural resources of the indigenous people. Linking the natural world and human activities helps promote interest in preserving ecosystems and biodiversity (Real, 2009). The participation of indigenous people in the design of tools for conservation will improve the level of acceptance toward management proposals (Herlihy & Knapp, 2003). Thus, "The Forest Pulse" could become a useful tool for the scientific analysis of the rainforest in the Western Guyana Shield, but also for the management of its use by indigenous people. It is our intention to make hard copies of "The Forest Pulse" available to the participant communities, jointly with meaningful information about relationships found between land classes and uses. Our results show that TEK-based approaches can serve as a basis for validating the livelihood relevance of a landscape classification. "The Forest Pulse" is freely available to any user, in raster format for GIS, in Supplementary Material 2.

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RESUMEN

Utilización de conocimiento indígena para relacionar el mapeado hiper-temporal de coberturas de suelo con el uso del territorio en el Amazonas venezolano: "El Pulso del Bosque". La teledetección y el conocimiento ecológico tradicional (CET) se pueden combinar para avanzar en la conservación de regiones tropicales remotas como la Amazonía, donde la toma de datos intensiva in situ a menudo es imposible. Integrar el CET en el seguimiento y el manejo de estas áreas permite la participación de la comunidad, y ofrece nuevos puntos de vista sobre el uso sostenible de los recursos naturales. En este estudio se desarrolla un mapa de cobertura del suelo del Escudo Guayanés (Venezuela), con una resolución espacial de 250 m, basado en datos de teledetección, y se utiliza el CET para validar su relevancia en relación con la subsistencia

de los pueblos indígenas y el uso que éstos hacen del territorio. En primer lugar se ha empleado un índice de vegetación basado en teledetección hiper-temporal para realizar una clasificación del territorio. Durante una expedición fluvial de 8 días, a lo largo de 1300 km por áreas sin carreteras en el Estado Amazonas (Venezuela), se han visitado seis comunidades que han proporcionado datos geo-referenciados sobre sus actividades cinegéticas, pesqueras y agrícolas. Estos datos de CET se han superpuesto al mapa de clasificación, con el fin de relacionar las clases de coberturas con los usos indígenas. Se han caracterizado las clases de cobertura en función de patrones de cambio temporal del verdor y la topo-hidrografía, y se han propuesto 12 tipos de cobertura del suelo, agrupadas en cinco tipos principales de paisaje: 1) masas de agua; 2) campo abierto/márgenes del bosque; 3) bosques siempre-verdes; 4) bosques semi-caducifolios submontanos; y 5) bosques nublados. Cada clase de cobertura del suelo se ha identificado con un perfil pulsátil que describe cambios temporales en el verdor, de ahí que el mapa haya sido titulado “El Pulso del Bosque”. Estos perfiles de verdor han mostrado una tendencia ligeramente ascendente, durante el periodo 2000 a 2009, en las clases que representan pastizales y zonas de matorral, así como una tendencia ligeramente decreciente en las clases que representan bosques. Este hallazgo es compatible con la ganancia de carbono en los pastizales como consecuencia del calentamiento del clima, y también con una cierta pérdida de vegetación en los bosques. De este modo, nuestra clasificación muestra potencial para la evaluación de efectos futuros del cambio climático sobre el paisaje. Algunas clases han resultado estar significativamente relacionadas con la agricultura, la pesca, la caza como práctica general, y más concretamente con la caza de primates, de *Mazama Americana*, *Dasyprocta fuliginosa*, y *Tayassu pecari*. Los resultados demuestran la utilidad de las aproximaciones basadas en CET como base para validar la importancia del paisaje, en áreas con alto valor de conservación, para la supervivencia de las personas, lo que proporciona una base para avanzar en el manejo de los recursos naturales en estas regiones.

Palabras clave: Amazonía, conservación de los bosques, verdor, participación indígena, cobertura del suelo, uso del suelo, teledetección.

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APPENDIX 1

People of the indigenous communities sharing authorship

Cascaradura Community (Kurripaco ethnic background; Municipio Atabapo): Andrés Camico, Juanita Cardozo, Cirilo Alterio Cavi, Francisco Cuiche, Vifaida Cuiche, Yuraima Cuiche, Gerónimo Evaristo, Rosa Evaristo, Blair Ventura, Darcy Ventura, Santiago Ventura.

Niñal Community (Curripaco and Yeral ethnic backgrounds; Municipio Río Negro): José Camico, Lucila Camico, Mauricio Camico, Mirla Camico, Roberto Camico, Tito R. M. Camico, Nelson Dasilva C., Fabián García, Mario García, Mariluz Guaca, Alipio Guariello, Avilio López, Lizanía López, Óscar López C., Eddi Melguero.

Kurimakare Community (Curripaco ethnic background; Municipio Río Negro): Gerónimo Carlos, Dollas G., Eliodora García, José García, Pablo García, Yolanda García, Arcenio M., Tuna Mutica, Mariemy Pesqueva, Carolino S., Avelino G. Sandoval, Claudia Sandoval, Clemente Sandoval, Esther Sandoval, Leonardo Sandoval, Pedro Lino Sandoval, Plinio Sandoval, Robert Sandoval, Sofia Sandoval, Marcino Sandoval.

Chapazón Community (Yeral ethnic background; Municipio Río Negro): Miriam Melguero, Carlos Pereira, Egídio Pereira, Onoria Pereira.

Solano Community (Baré ethnic background; Municipio Río Negro): Manuel Francisco García, Simón García, Julieta Surbisana.

Guzmán Blanco Community (Baniva Curripaco and Warekena ethnic backgrounds; Municipio Maroa): Edilto Bernabé, María Esperanza Bernabé, Paublina Bernabé, Uliezar Bernabé, Cheila Ch. M., Milagro de Churuaidare, Hermes Churuo, Martina García, Maricela Garrido, M.R.C. José A., Ilda Martina, Anabel Mure, Fani María Mure, Yendri Yumileth, Karina Yuriyuri, Juana Yuriyuri.