**Research Article**

# Classification of landscape types based on land cover, successional stages and plant functional groups in a species-rich forest in Hainan Island, China

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**Abstract**

Large-scale identification of landscape types in species-rich forest ecosystems is a challenge to landscape designers and forest ecologists. With a systematic grid-sample-plot investigation and landscape-attributes extraction of SPOT-5 imagery in a tropical forest region in Hainan Island, China, we developed a landscape classification system of land cover, successional stages, and dominant plant functional groups in species-rich forest ecosystems. We classified the study landscape into eight land cover types, four successional stages, and six functional patch types, with accuracies at ≥ 78%. The patches dominated by the pioneer functional groups were mainly distributed in areas of early recovery stages on sunny slopes at elevations < 850 m, while the climax functional groups had more occupancies in the late recovery stages on shaded slopes at elevations > 850 m. The slope gradient had no significant influence on the patch distribution patterns in the study region. Our results show that species-rich forest landscapes can be classified into patch types of different dominant functional groups and successional stages through remote sensing in conjunction with ground survey and GIS.

**Key words:** vegetation type, recovery stages, tropical forest, remote sensing, GIS.

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## Introduction

Tropical forests are among the most complex ecosystems on Earth, playing vital roles in biodiversity conservation and global ecological functioning. Although many aspects of tropical forest ecosystems have been studied, there are still knowledge gaps about their structures and function, especially at large scales [1]. High technologies such as remote sensing (RS) and geographical information systems (GIS) have made it possible to identify forest landscape attributes at a variety of spatial scales. RS technology has been successfully used in the classification, mapping and monitoring of forest landscapes in the temperate and cold temperate regions [2-5]. However, the application of RS for landscape studies in species-rich forest ecosystems, such as in the tropical rainforest and sub-tropical evergreen-broadleaved forest, has proven a great challenge. This is mainly because those forests have high species diversity and very complex structural features, and frequent cloudy days and lack of ground-based information often cause great difficulties in discerning and interpreting RS imagery. Some attempts at classification of tropical forest landscape types through RS have had promising outcomes. For example, Sánchez-Azofeifa et al. [6] classified the forest landscape simply into forest and non-forest by RS in order to study and monitor the effects of logging on landscape fragmentation. Similarly, based on recovery stages, Foody et al. [7] classified a tropical forest into five types, i.e. < 2 years, 2-3 years, 3-6 years, 6-14 years and >14 years, with a total accuracy of 79%.

The relationships between species diversity and ecosystem functioning have become a most important topic in ecology in recent years [8, 9], but the ecological functioning of diversity at landscape scale is still not well understood [10]. Functional group (FG) is defined as a group of species that play similar roles in an ecosystem [11]. The FG approach is an effective way of linking the compositions of complex ecosystems (such as tropical forest) with their ecological functions [12]. Landscape classification based on FG is a new way to identify patch types in species-rich and structurally-complex tropical forest regions. Study of FG on a landscape scale could explain how diversity varies with the environmental factors at large scales. In the early 1970s, Mueller-Dombois and Ellenberg [13] tried to classify vegetation types based on the functional similarities between different ecosystems. Paruelo et al. [14], in their studies on the functional heterogeneity of vegetation in South American temperate regions, proposed the concept of ecosystem functional types (EFTs), and identified 19 EFTs in their study area by using NOAA/AVHRR imagery. Similarly, studying the spatiotemporal pattern of local ecosystems with rapid urban expansion in the Phoenix metropolitan landscape, Wu et al. [15] also adopted the EFTs approach to build a hierarchical patch dynamic model. Bonan and Samuel [16] proposed that landscapes are patch mosaics composed of dominant plant functional types, and applied their 15 plant functional types to a global vegetation dynamics model. Most of the vegetation classifications based on FG have been in the temperate regions or on a global scale, but information is lacking about tropical forest landscapes.

Studies of the relationships between species distribution pattern and environmental factors could reveal the drivers of variation in vegetation or ecosystems. Insightful knowledge of such relationships can be gained only at landscape, regional or global scales [17]. Hara et al. [18] recognized that on the regional or global scale, zonal climatic conditions are the major determinants of the distribution of plant species, life forms, and vegetation types, while within the same climatic zone, topography is a major factor in determining the patterns of vegetation distribution. In recognition of the importance of topography in influencing vegetation distributions, much attention has been paid to analyzing the landscape patterns and topographical variations [19, 20]. The variation of vegetation types along the environmental gradient could be better understood by the overlay technique in GIS [21, 22]. Research on the relationships between species distributions and environments based on FG could help us to understand the driving forces of vegetation changes and their spatial heterogeneity on a landscape scale [23].

Hainan Island is located in the southern part of China, where tropical forests are distributed on the northern edge of tropical Asia in a forest ecosystem with the greatest biodiversity in China. Starting in the 1950s, tropical forest resources declined sharply due to the pressure of population growth and economic development. Over-exploitation has greatly changed landscape patterns in the tropical forest regions of Hainan Island. Extensive deforestation and long-term intensive agricultural land use have greatly reduced the area of primary forests, resulting in landscape mosaics of a few old-growth forest patches dispersed in the large matrix of degraded ecosystems at various recovery stages [24]. There have been some ecological studies on the primary or old-growth forests [25], but we still know little about those degraded by anthropogenic disturbance. In this study, we conducted an intensive field survey with 149 systematic-grid sampling plots among the natural landscapes in the Bawangling tropical forest region of Hainan Island. Our objectives were to address the following questions: 1) would it be possible to classify landscape types based on FGs in the species-rich tropical forest ecosystems through RS? 2) would it be possible to interpret tropical forest patch types of different recovery stages through RS? and 3) How would the landscape types classified by FGs change along the topographical and successional gradients?

## Methods

*The study site*

The study area is located in the Bawangling forest region (18°53′-19°20′N，109°05′-109°53′E), Hainan Province, China, covering an area of *ca.* 48,000 ha (Fig. 1). The elevation of the region ranges from *ca*. 50 m to 1,654 m a.s.l. The region is characterized by a tropical monsoon climate with a distinct wet season from May to October and a dry season from November to April. The mean annual precipitation is 1,677 mm, and the mean annual temperature is 24.2℃. Soils at higher elevations are a complex of red loam and yellow loam, while latosol developed from granite dominates soils at lower elevations.

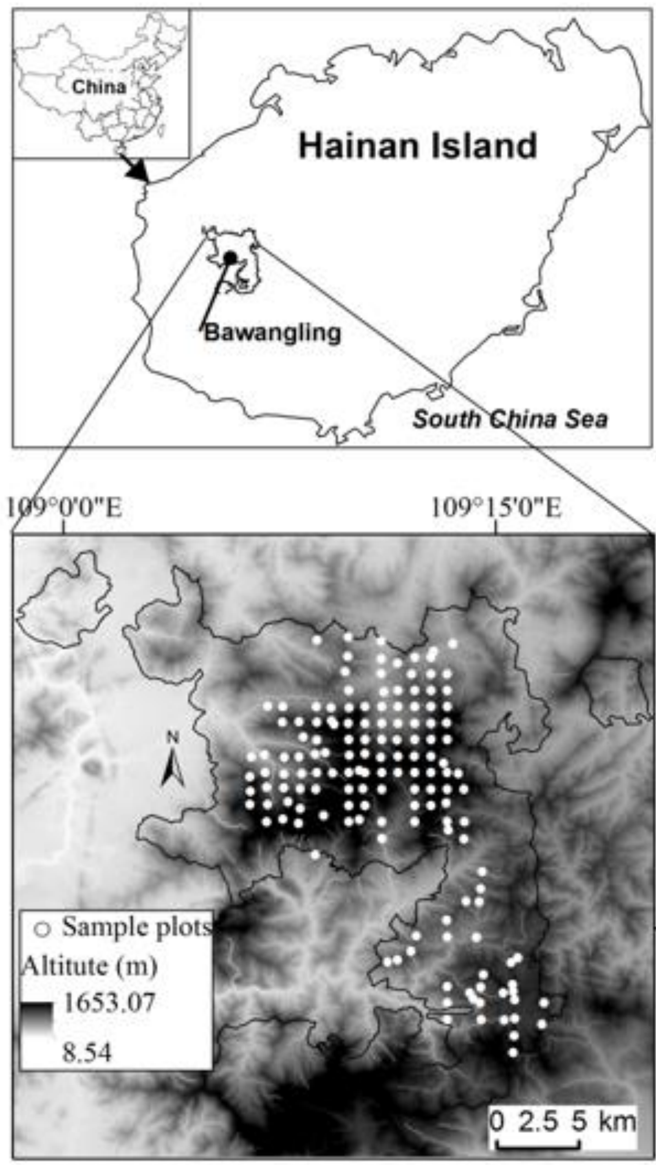


**Fig. 1. Design of field survey sample plots in the tropical forest region of Bawangling, Hainan Island, China**

Five natural climax vegetation types are found in this region: the tropical lowland rainforest (TLF), the tropical montane rainforest (TMF), the tropical monsoon rainforest (MSF), the montane dwarf forest (MDF), and the tropical coniferous forest (TCF). TLF is dominated by tree species such as lychee (*Litchi chinensis*), kalladamba (*Homalium ceylanicum*), and narig (*Vatica mangachapoi*), with a diverse array of co-occurring species. Some big canopy species, including malur (*Dacrydium pectinatum*), spicewood (*Lindera kwangtungensis*), and blakei oak (*Cyclobalanopsis blakei*), dominate the TMF. The dominant species in the MSF include goden stem (*Peliophorum tonkinense*), sweetgum (*Liquidambar formosana*), and tree cotton (*Gossampinus malabarica*). The dominant species in MDF include isu tree (*Distylium racemosum*), cluster-flowered sweetleaf (*Symplocos poilanei*), and caylon cinnamon bark (*Cinnamomum tsoi*). TCF is dominated by tenasserim pine (*Pinus latteri*) and often has some broadleaved species under the canopy layer, such as *narig*, assamese oak (*Quercus vestita*), and yandouke (*Lithocarpus corneus*). Prior to 1957, most of the Bawangling forest region was covered by the above-mentioned types of old-growth tropical forests. Before the 1960s, deforestation occurred due mainly to natural disturbances such as fire, strong monsoon winds, insects, and traditional shifting cultivation by the local people. From the 1960s onwards commercial timber harvesting became the major cause of deforestation [24]. In the 1980s, because of decreased tropical forests, timber harvest changed from clear cutting to selective logging. Since 1994, timber harvest has been banned in order to protect and restore the degraded forests. Because of severe and repeated anthropogenic disturbances over the past forty years, forest landscapes in Bawangling have become increasingly fragmented, and the old-growth forests were displaced by vegetation types of early successional stages, such as secondary forests of various recovery stages, shrub/grass land, and even bare land. Some bare or shrub/grasslands have been converted to forest plantations. At present, the landscape in the Bawangling forest region is a mosaic of natural vegetation and plantations, in which natural forests still occupy a greater area.

*Remote sensing imagery preprocessing*

SPOT-5 image (pass 124/ row 47), acquired on November 29, 2006, was used in this study. It was geometrically rectified using control points taken from topographic map at 1:10,000 scale. We used a nearest-neighbor re-sampling technique and obtained a root mean square error with less than 1/2 pixel. The projection coordinate system of the rectified image was Transverse Mercator, the Spheroid Name was Krasovsky, and the pixel size was 10×10 m. After the geographical referencing and geometrical corrections, the imagery was cropped to the area of interest, and a cloud and cloud-shadow mask was manually built through visual interpretation and applied, providing an image ready for classification analysis.

*Field data collection*

A total of 149 sample plots (each with a size of 20×20 m) were laid systematically over the forest region (Fig. 1). At each connecting-point of four neighboring grid cells, a plot was established for vegetation survey. Within each sample plot all free-standing woody stems with diameter at breast height (DBH) ≥1cm were counted, measured, and identified to the species level. We also recorded the height and canopy size of free-standing woody plants. We determined the time since the last disturbance and the disturbance type on each sample plot, using the timber-logging archives of the Forestry Bureau of Bawangling. In addition, we interviewed experienced loggers for detailed information on harvesting operations.

*Landscape classifications*

The landscape classification was made in four steps: (1) description of landscape types of the whole study area based on land use/cover; (2) classification of natural forest landscape types in the study area based on recovery stages; (3) classification of natural forest landscape types based on dominant FGs; and (4) overlay of (2) and (3).

Forest landscape types in the study area include the fragments of old-growth forests and secondary forests developed at various stages. The land use/cover could be classified into the following types: natural broadleaved mixed forest (NB), natural pine forest (NP), shrubland (SR), grassland (GR), pine plantation (MP), plantation of broadleaved trees (MB), water (WA), and others (OT). As most of the natural forest landscapes experienced severe disturbances and are now in different recovery stages, our field investigation divided the natural forests (including natural pine forest and rainforest) into four recovery stages: <10 years (I), 11-20 years (II), 21-35 years (III), and ≥36 years inclusive of old-growth (IV). The natural forest landscape was classified into six classes of dominant FGs (grass dominated land (F1), pioneer shrub dominated land (F2), pioneer sub-canopy tree dominated forest (F3), pioneer canopy tree dominated forest (F4), climax sub-canopy tree dominated forest (F5), and climax canopy tree dominated forest (F6)).

Using our field data on woody plant species composition, we adopted the FG classification methods of Köhler et al. [26], classifying FGs based on the potential maximum height and successional status of the species. The species were grouped into pioneer or climax according to their successional status, and classified into three height classes (shrub 2-5 m, sub-canopy 5-15 m, and canopy 15-40 m) according to potential maximum height. Thus, six FGs for free-standing woody plants were defined according to the combination of the two criteria: pioneer shrub, climax shrub, pioneer canopy tree, pioneer sub-canopy tree, climax sub-canopy tree, and climax canopy tree functional group. Importance value (= relative frequency + relative abundance + relative basal area) was used to compare the relative dominance of different FGs in a sample plot. The plots with similar importance value ratios of FGs were aggregated into the same landscape types.

The FGs for all the vegetation types except the climax shrub had different numbers of sample plots. Climax shrub occurs in the understory of the canopy tree layer, so it generally shows no dominance in either the old-growth or the disturbed sites. Thus, the climax shrub could not be treated the same as the other five FGs in the landscape classifications by RS. The landscape classification systems used this study are described in Table 1.

**Table 1.** The classification system of landscape types based on land use/cover, recovery stages and dominant functional groups respectively in the tropical forest region of Bawangling of Hainan Island, China

| Landscape components | Code |
|---|---|
| Land use category | |
| Natural *Pinus Latteri* forest | NP |
| Natural broadleaved mixed forest | NB |
| Shrubland | SR |
| Grassland | GR |
| Pine plantation | MP |
| Plantation of broadleaved trees | MB |
| Water | WA |
| Others (including villages, roads and bare lands) | OT |
| Recovery stages | |
| Secondary forest, ≤10 years | I |
| Secondary forest, 11-20 years | II |
| Secondary forest, 21-35 years | III |
| Forest, ≥36 years | IV |
| Dominant functional groups | |
| Grass | F1 |
| Pioneer shrub | F2 |
| Pioneer sub-canopy tree | F3 |
| Pioneer canopy (including emergent) tree | F4 |
| Climax sub-canopy tree | F5 |
| Climax canopy (including emergent) tree | F6 |

*Supervised classification*

We adopted the maximum likelihood supervised classification method [6] to make landscape classifications on the SPOT-5 imagery. Training sample plots of each landscape type were randomly selected to define signatures so that pixels of same characteristics could be identified and grouped automatically based on the signatures. The images were all treated with a 5×5 low-pass (mean) filter for reducing within-class variance and increasing the spectral distinction of vegetation types [27]. The geo-referenced ground points from the field grid survey were used as references for landscape types and spatial locations. The training samples were selected and the classification signatures were established for each landscape type by the AOI (area of interest) in ERDAS IMAGE 8.5 [28]. The spectral separability among the training samples was evaluated to obtain more accurate values of the training samples. Only when the separability of two training samples was high enough (≥10) could the classification be reasonably made. The final classification characteristics were determined through repeated operations of the program. Based on the collections of training samples, the maximum likelihood and parallel-piped decision rules were used to analyze each pixel and aggregate the pixels into different types of training samples, and the landscapes were preliminarily classified into different types on a map. Due to the interference of cloud and haze, some patches in the classification were false overshadows of clouds. To overcome this problem, we made these patches into real types based on the field investigation plots. Some non-identifiable patches were judged by expert knowledge or grouped with neighboring most probable patch types. All fragments ≤0.45 ha (5 pixels in the image) were eliminated from the analysis.

The accuracy of the classification was determined by the Overall Accuracy (AC) test and the Kappa Analysis [7]. AC is the ratio of pixels correctly classified to the total reference pixels. The greater AC value indicates more accurate classification. The classification is considered to be acceptable when the AC≥70% [29]. The Kappa coefficient quantifies the overall accuracy in a contingency table relative to that expected by chance; the formula is as follows:

$$k = \left( N \sum_k X_{kk} - \sum_k \left( X_{k+} X_{+k} \right) \right) \Big/ \left( N^2 - \sum_k \left( X_{k+} X_{+k} \right) \right)$$

where $k$ is Kappa value, $N$ is total number of pixels in all ground truth classes, $\sum X_{kk}$ is the sum of the confusion matrix diagonal classes, $X_{k+}$ is the sum of the ground truth pixels in that class, $X_{+k}$ is the sum of the classified pixels in that class [30]. $k$ varies between 0-1.

*Calculation of the area percentages of different landscape types*

The area percentages of different landscape types dominated by different FGs and in different recovery stages were calculated in ArcGIS 8.3 [31]. The landscape map classified by dominant FGs was transformed into grid format. Relationships between landscape types dominated by different FGs and topographical factors were examined by cross tabulation of land cover map with maps of elevation, slope and aspect. Chi-square analysis was performed to test the independence of landscape types dominated by different FGs and topographical factors. The digital elevation model (DEM) was produced by a 1:10,000 digital topographical map, assisted by the interpolation program ANUDEM 4.6 [32]. In this study, the elevation was classified into six classes: 1 for < 450 m, 2 for 450-650 m, 3 for 650-850 m, 4 for 850-1,050 m, 5 for 1,050-1,250 m and 6 for > 1,250 m. The slope was classified into seven classes: 1 (< 6°), 2 (6-15°), 3 (15-25°), 4 (25-35°), 5 (35-45°), 6 (45-55°), and 7 (>55°). The aspects were classified into five classes: 1 for flat area (0°), 2 for semi-shaded slopes, including east (67.5-112.5°) and northwest (292.5-337.5°), 3 for shaded slopes, including north (0-22.5° and 337.5-360°) and northeast (22.5-67.5°), 4 for semi-sunny slopes, including west (247.5-

292.5°) and southeast (112.5- 157.5°), and 5 for sunny slopes, including south (157.5-202.5°) and southwest (202.5- 247.5°).

## Results

*Evaluation of the classification accuracy*

The landscape types in the study area were interpreted on the imagery by the supervised classification. The accuracies of the three classification schemes were all over 78.0% (Tables 2-4). The overall Kappa statistics in the classification by the recovery stages were 67.2%, and all were over 80% in the other two classification schemes. In the three classification schemes, the highest classification accuracy was obtained by the land-use approach, followed by the dominant FGs and the recovery stages. The user's accuracy (UA) and the producer's accuracy (PA) were different among the three schemes. In the scheme by land use, with exception of the MP, the UA and the PA were 73.6% and 79.0% respectively, and the values were all over 85.0% in the other land use types (Table 2). In the scheme by the recovery stage, the relatively younger recovery stages (I and II) had lower UA and PA, while the relatively older recovery stages had greater UA and PA (all over 78.0%) (Table 3). In the scheme based on dominant FGs, except that F4 had a greater PA (81.4%), the patch types (F2, F3 and F4) dominated by the pioneer woody plant FGs all had relatively lower UA and PA. The patches types (F5 and F6) dominated by the climax woody plant FGs and F1 had relatively greater UA and PA (all over 76.0%) (Table 4).

**Table 2 -** Classification error matrix by land use/cover class based on the maximum likelihood classification of a 5×5 smoothed SPOT imagery

| Classified data | Reference data | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | NP | NB | SR | GR | MP | MB | WA | OT | ∑ | User's accuracy (%) |
| NP | 230 | 0 | 0 | 0 | 12 | 0 | 0 | 0 | 242 | 95.0 |
| NB | 1 | 83 | 0 | 0 | 4 | 0 | 0 | 0 | 88 | 94.3 |
| SR | 0 | 0 | 70 | 6 | 0 | 0 | 0 | 3 | 79 | 88.6 |
| GR | 0 | 0 | 4 | 68 | 0 | 0 | 0 | 8 | 80 | 85.0 |
| MP | 20 | 2 | 1 | 0 | 64 | 0 | 0 | 0 | 87 | 73.6 |
| MB | 1 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 51 | 98.0 |
| WA | 0 | 0 | 0 | 0 | 1 | 0 | 75 | 2 | 78 | 96.2 |
| OT | 0 | 0 | 2 | 4 | 0 | 0 | 5 | 109 | 120 | 90.8 |
| ∑ | 252 | 85 | 77 | 78 | 81 | 50 | 80 | 122 | 825 | |
| Producer'saccuracy (%) | 91.3 | 97.7 | 90.9 | 87.2 | 79.0 | 100 | 93.8 | 89.3 | | |
| Accurately classified pixels (along diagonal) | | | | | | | | 749 | | |
| Total number of pixels used for reference | | | | | | | | 825 | | |
| Overall classification accuracy | | | | | | | | 90.8% | | |
| Over Kappa statistics | | | | | | | | 89.0% | | |

Codes in Table 2 are listed in Table 1.

**Table 3.** Classification error matrix with recovery stage class based on the maximum likelihood classification of a 5×5 smoothed SPOT imagery

| Classified data | Reference data | | | | | |
|---|---|---|---|---|---|---|
| | I | II | III | IV | ∑ | User's accuracy (%) |
| I | 91 | 33 | 7 | 0 | 131 | 69.5 |
| II | 29 | 92 | 47 | 2 | 170 | 54.1 |
| III | 8 | 8 | 433 | 46 | 495 | 87.5 |
| IV | 0 | 0 | 68 | 261 | 329 | 79.3 |
| ∑ | 128 | 133 | 555 | 309 | 1,125 | |
| Producer's accuracy(%) | 71.1 | 69.2 | 78.0 | 84.5 | | |
| Accurately classified pixels (along diagonal) | | | | | | 877 |
| Total number of pixels used for reference | | | | | | 1,125 |
| Overall classification accuracy | | | | | | 78.0% |
| Over Kappa statistics | | | | | | 67.2% |

Codes in Table 3 are listed in Table 1.

**Table 4.** Classification error matrix with dominant functional groups class based on the maximum likelihood classification of a 5×5 smoothed SPOT imagery

| Classified data | Reference data | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | F1 | F2 | F3 | F4 | F5 | F6 | ∑ | User's accuracy (%) |
| F1 | 140 | 7 | 0 | 0 | 0 | 0 | 147 | 95.2 |
| F2 | 9 | 20 | 8 | 0 | 2 | 0 | 39 | 51.3 |
| F3 | 0 | 7 | 57 | 4 | 7 | 6 | 81 | 70.4 |
| F4 | 0 | 0 | 11 | 35 | 1 | 0 | 47 | 74.5 |
| F5 | 0 | 0 | 4 | 1 | 65 | 6 | 76 | 85.5 |
| F6 | 0 | 0 | 0 | 3 | 10 | 151 | 164 | 92.1 |
| ∑ | 149 | 34 | 80 | 43 | 85 | 163 | 554 | |
| Producer's accuracy (%) | 94.0 | 58.8 | 71.3 | 81.4 | 76.5 | 92.6 | | |
| Accurately classified pixels (along diagonal) | | | | | | | 468 | |
| Total number of pixels used for reference | | | | | | | 554 | |
| Overall classification accuracy | | | | | | | 84.5% | |
| Over Kappa statistics | | | | | | | 80.3% | |

Codes in Table 4 are listed in Table 1.

*Area percentage of different landscape types*

The study area covers 48,234.5 ha, in which NB was the most dominant landscape type (74.6%) and NP the second largest landscape type (10.8%), while the remaining landscape types collectively accounted for only about 14.6% of the study area (Table 5). Natural forests (including NB and NP) accounted for 85.4% of the total area of the study region. In the natural forest landscapes, the area percentages accounted for by the patch types of different recovery stages were 17.1% for <10 years, 50.8% for 11-20 years, 21.7% for 21-35 years, and 10.4% for ≥36 years.

**Table 5 -** Areas of land use category in the research region of Bawangling, Hainan Island, China

| Land use/cover category | Area ($hm^2$) | Percent of area (%) |
|---|---|---|
| NP | 5,186.6 | 10.8 |
| NB | 35,995.1 | 74.6 |
| SR | 1,811.4 | 3.8 |
| GR | 1,207.7 | 2.5 |
| MP | 1,816.7 | 3.8 |
| MB | 838.8 | 1.7 |
| WA | 1,123.1 | 2.3 |
| OT | 255.1 | 0.5 |
| Total | 48,234.5 | 100 |

Codes in Table 5 are listed in Table 1

In the natural vegetation landscapes (natural forests, shrubland, and grassland), which accounted for 91.7% of the total study area, the area percentages occupied by the patch types dominated by different FGs were: F1 2.9%, F2 6.6%, F3 23.0%, F4 19.1%, F5 32.6%, and F6 15.8%.

Overlay of the landscape classification map based on recovery stages with that based on dominant FGs produced the natural landscape mosaics of patches dominated by different FGs in different periods of recovery (Fig. 3). Pioneer sub-canopy tree and pioneer canopy tree dominated the natural secondary forest of recovery time <10 years, and accounted for 33.7% and 49.4% of the areas in this landscape type (Fig. 2). In the natural secondary forest with recovery time from 11-20 years, pioneer canopy tree, climax sub-canopy tree and pioneer sub-canopy tree dominated, accounting for 39.5%, 33.4% and 18.6% of the landscape area. In the natural secondary forest with recovery time from 21-35 years, climax sub-canopy tree apparently dominated, accounting for 68.3% of this landscape area. Also, in the natural secondary forest of recovery time ≥ 36 years, climax canopy tree dominated the landscape, accounting for 76.2% of the area (Fig. 2). The statistics for areas dominated by different FGs revealed that the pioneer groups occupied more area in the early recovery stages, while the climax groups dominated the landscapes in the later recovery stages.

*The relationships between landscape pattern and topographical factors*

Elevation had a significant influence on the distribution of patches dominated by different FGs (Chi-square; $P<0.001$). The patches dominated by grass had relatively high distributions in the elevation range of 650-1,250 m (Table 6). Patches dominated by pioneer shrub had relatively high area percentages in the range of 850-1,250 m. The variations of the patch types dominated by the pioneer sub-canopy tree and by the pioneer canopy tree were similar along the elevation gradient. Their areas decreased gradually with increasing elevation. Contrarily, patches dominated by the climax sub-canopy tree and by the climax canopy tree increased with increasing elevation. Generally, the landscape of altitude ≤ 850 m was mainly dominated by the pioneer FGs, while the climax FGs dominated the landscape of altitude ≥ 1,050 m.

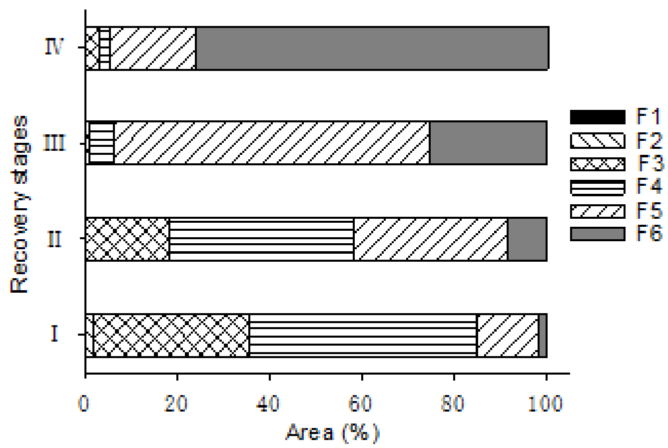


**Fig. 2. The area proportions of different functional group dominated patches in different recovery stages in the study area**
**Codes on the Fig. 2 are listed in Table 1.**

Chi-square analyses indicated that aspect had a significant influence on the distribution of patch types dominated by different FGs ($P<0.001$) except grass ($P>0.05$). Analysis of the aspect gradient (Table 6) showed that the patches dominated by grass distributed almost evenly in every class of aspect. Pioneer shrub had relatively greater distributions in the flat, semi-sunny and sunny slopes (the area percentage was 10.3%, 7.2% and 9.8%, respectively). The patch types dominated by pioneer trees also had relatively greater percentages of area in the flat, semi-sunny and sunny slopes (for pioneer sub-canopy tree, 20.1%, 25.6% and 27.0% respectively; for pioneer canopy tree, 25.2%, 20.3% and 30.8% respectively). In contrast, the climax FGs dominated the landscape patches in the semi-shaded and shaded slopes (for climax sub-canopy tree, 34.2% and 35.4% respectively, while for climax canopy tree ,28.2% and 25.9% respectively).

The slope class displayed no significant influence on the distribution patterns of patch types dominated by different FGs (Chi-square; $P>0.05$). Every FG distributed almost evenly on different slope classes (Table 6).

**Table 6 -** Area proportions of patch types dominated by different functional groups along the elevation, slope and aspect gradients

| | Patch types dominated by different functional groups | | | | | |
|---|---|---|---|---|---|---|
| | F1 | F2 | F3 | F4 | F5 | F6 |
| Elevation (m) | | | | | | |
| < 450 | 1.35 | 8.47 | 33.36 | 25.66 | 18.73 | 13.44 |
| 450-650 | 1.21 | 8.06 | 26.11 | 27.75 | 23.82 | 13.05 |
| 650-850 | 3.53 | 4.89 | 24.87 | 22.36 | 25.94 | 18.41 |
| 850-1050 | 4.87 | 13.51 | 14.61 | 19.24 | 27.31 | 20.47 |
| 1050-1250 | 4.16 | 11.14 | 14.29 | 11.81 | 36.15 | 22.44 |
| > 1250 | 0.18 | 1.63 | 11.60 | 5.23 | 49.31 | 32.05 |
| Slope (degree) | | | | | | |
| < 6 | 3.20 | 6.63 | 24.24 | 21.31 | 29.63 | 14.99 |
| 6-15 | 2.31 | 5.71 | 22.20 | 19.77 | 31.32 | 18.68 |
| 15-25 | 2.56 | 6.46 | 21.94 | 19.40 | 31.64 | 17.99 |
| 25-35 | 2.58 | 6.47 | 22.34 | 19.59 | 31.47 | 17.54 |
| 35-45 | 2.46 | 6.84 | 22.97 | 18.94 | 32.40 | 16.39 |
| 45-55 | 2.65 | 7.07 | 22.93 | 18.07 | 33.10 | 16.18 |
| >55 | 3.29 | 6.77 | 23.12 | 18.99 | 33.03 | 14.81 |
| Aspect class | | | | | | |
| Flat | 2.96 | 10.34 | 20.15 | 25.25 | 29.71 | 10.60 |
| Semi-shaded | 2.92 | 5.33 | 13.07 | 16.36 | 34.16 | 28.15 |
| Shaded | 2.06 | 4.29 | 16.44 | 15.88 | 35.44 | 25.89 |
| Semi-sunny | 3.14 | 7.19 | 25.56 | 20.26 | 30.98 | 12.87 |
| Sunny | 2.72 | 9.80 | 26.96 | 30.77 | 15.00 | 14.77 |

## Discussion

*The landscape classification*

The transformation of remote sensing data into thematic classification maps generally needs two steps. The first is the spectral signature interpretation of reference classes of the images, and the second is the extrapolation of the defined spectral characteristics to the whole study area [33]. The accuracy of the final classification is closely correlated with the two steps. The spectral signature interpretation of images for the species-rich and structurally complex natural tropical forest region is much more difficult and complicated than in other regions. More attention should be paid to the spectral variability in the supervised classification, which requires more information about on-the–ground, actual categories. The many widely covered field grid sample plots in the study region have helped us to define the actual field attributes of different vegetation types and to identify the right categories of patches on the remote sensing images. This method provides for less labor-intensive, easier interpretation of landscape types through RS and GIS tools that are very useful in vegetation classification, land-use planning, biodiversity conservation, and other management activities on large landscape scales in species-rich and structurally complex ecosystems.

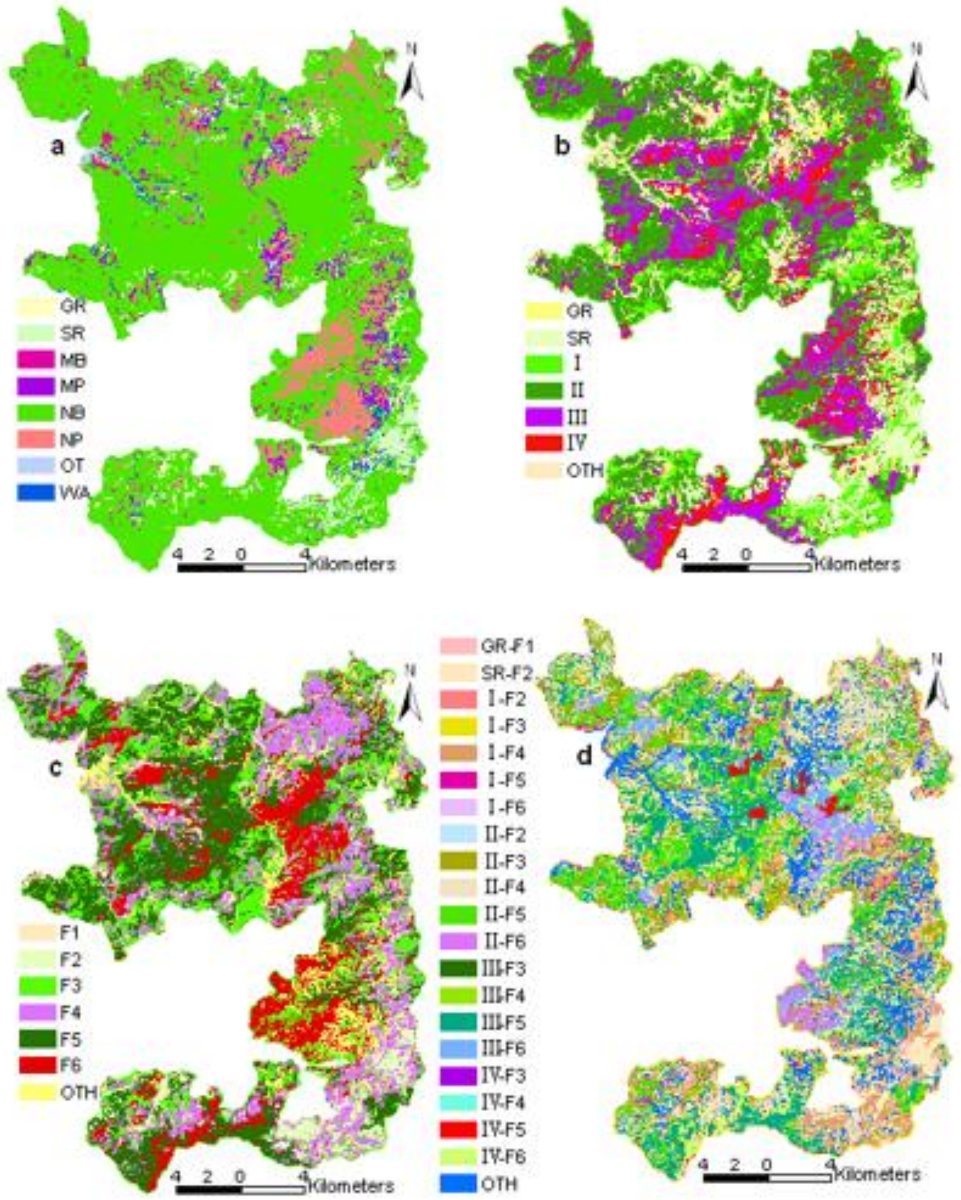


**Fig. 3. The landscape classifications based on land use/cover (a), recovery stages (b), dominant functional groups(c), and by overlay of (b) and (c) in the study area**
**Codes are listed in Table 1; "OTH" in (b), (c) and (d) refers to non-natural vegetation patches.**

The overall accuracy of the classification scheme based on land use/cover was 90.8% (Table 2), mainly due to the significant spectral separability differences among the land use categories. Other studies have achieved similar accuracy of imagery classification. For example, based on multi-date Landsat TM imagery, Tottrup [34] classified the tropical forest landscape into six types (*i.e.,* old-growth, Karst, deciduous, second-growth, bamboo, and shrub), with a total accuracy of ~91%. The natural pine forest and the pine plantation had similar spectral signatures on the images, so there was some confusion of image pixels representing these two land use categories. The producer's accuracy for the 81 pine plantation pixels was 79%, with 12 pixels being misinterpreted as natural pine forest (Table 2).

Compared to the classification scheme based on land-use types, the classification scheme based on recovery stages for natural forests was much more difficult. The overall accuracy of this scheme was 78.0% and the overall Kappa index was 67.2% (Table 3). Our classification accuracy is similar to Hernandez-Stefanoni's study [35]. He identified four recovery stages in a tropical forest area based on TM imagery with a total accuracy of 82%. We can see that confusion between the adjacent classes was relatively high, probably due to the similarity of composition and structure of adjacent classes and the relatively low spectral separability between them. A similar phenomenon has been found in other studies [7, 36]. In order to reduce the confusion between adjacent recovery stages, Steininger [36] merged the adjacent classes and classified the secondary forests into two recovery stages of < 13 years and 13-19 years. The spectral separability of the earlier recovery stages (I and II) was lower than the later recovery stages (III and IV) in our study, mainly due to wider variation in spectral signatures of the earlier recovery stages than of the later ones. A similar phenomenon was found by Foody et al. [7]. Some studies found it difficult to separate the natural secondary forests of recovery time ≥ 20 years with the old growth through the TM imagery [36, 37]. However, in our study for the tropical forest landscape, the natural secondary forests of recovery time ≤ 35 years could be separated from the old growth forest with acceptable accuracies through the 5×5 low-pass mean filter on images, based on the large scale field sample plot investigation for the vegetation. Lucas et al. [38] classified a tropical forest into four recovery stages by using the NOAA /AVHRR imagery, with an overall accuracy of less than 60%. He reasoned that the low accuracy was due to the lack of knowledge about the tropical forest characteristics of different recovery stages, and few field sample investigation plots were available to help his corrections. The chemical components, anatomical structure and water contents of leaves [39], and the species composition, vertical structure and canopy architecture of communities among different recovery stages were different. In the study, the reason for separating different recovery stage types on SPOT-5 image was due to differences of spectral reflectance resulting from the combined effects of the previously mentioned factors.

The classification of forest landscape types is usually based on the dominant species in different forest communities [40], which is suitable for species-poor and structurally simple forest ecosystems such as those in cold temperate or temperate regions. However, this classification method is often not applicable in species-rich and structurally complex forest ecosystems of tropical and subtropical forest regions, where dominant species are usually not obvious and hard to assess. We tried to identify the dominant species by calculating the importance value of the component species in our sampling plots, but did not find significant differences in the importance values for many species in the plots of late recovery stages. Therefore, it would be impossible to classify the tropical forest landscape types in our study area by the dominant species approach. Also, traditional forest classification methods such as the physiognomy approach could not reflect anthropogenic disturbances that strongly influence the functioning and dynamics of ecosystems [14]. The landscape classification approach based on FGs can reflect the responses of organisms or groups of organisms to environmental changes, which would be useful in planning and monitoring for biodiversity and forest management. The classification system with RS techniques could provide better understanding of the response of dominant FGs to major anthropogenic and natural disturbance regimes and to changing environmental factors [14]. Detailed studies are needed on these aspects of tropical forest ecosystems and their dynamics.

In this study, we attempted to make supervised classification of the remote sensing images based on dominant FGs. This classification has produced a reasonable result with acceptable accuracies (Table 4). Our results showed that the classification accuracies based on the climax FGs (F4 and F5) were better than those based the pioneer ones (F1, F2, and F3), which also indicated that the spectral variability within pioneer classes was more dynamic and unstable, and the similarities between adjacent classes were relatively high, so misinterpretations were more likely to occur. Some further separability is possible with the aid of contextual and ancillary information, and further discrimination would likely be possible using data acquired in additional wavebands [41].

*Distribution patterns of different landscape types*

Our study area was covered by 85.4% natural forests composed of forest patches in different recovery stages due to long-term, high intensity commercial logging and slash-and-burn agriculture. Most of the remnant old growth forests were in higher elevation, steep slope, not easily accessible sites. Compared with old growth forests, most of the existing forest ecosystems are degraded by severe disturbances. Their canopy structures have been changed drastically, changing available light, air temperature, humidity, and soil surface conditions under the forest canopy [42]. Therefore, the species composition, structure and corresponding functions of the ecosystems have changed greatly. We found that patch types dominated by different FGs changed along the spatial (i.e. topographical factors) and temporal (recovery period) gradients in the landscape. Each FG had its optimum ranges of distribution along the gradients of elevations, aspects and recovery stages. The slope in the study area had no significant influence on the distribution of patch types dominated by different FGs, likely because the slopes in the study area are not steep enough to cause great changes in ecological factors. The pioneer FGs had higher seed production and adaptability to full sunshine, higher intensity, and more frequent disturbances [43], with higher dominated patch area percentages in the shrublands, on flat and sunny slopes, at elevations of < 850 m, and in landscapes of early recovery periods. However, with the increase of recovery time, change of aspect from sunny to shadier, and increased elevation, the pioneer FGs were gradually replaced by the climax FGs. Because some pioneer canopy or sub-canopy species such as Hainan yangtong (*Adinandra hainanensis*), karnikar (*Pterospermum heterophyllum*), sweetgum usually have long life spans, they could survive and regenerate in the canopy gaps, thus coexisting for a long time with the climax FGs. The grass patch had relatively high area percentage in the elevation range of 650-1,250 m, mainly caused by grazing and hunting by indigenous people, who grazed their herds and flocks on the higher elevation ranges, where forest protection was relatively weak and they could set patches of forest on fire to favor grasses, which are more suitable for animal grazing and wildlife hunting.

The climax FGs were the main components of the forest region used in our study. Of the 578 species in our investigation sample plots, 89.6% were climax species. The climax FGs usually had some features different from the pioneer FGs and were distributed more on shady slopes, at higher elevation ranges and in the later recovery stages.

## Implications for conservation

In the present study, we developed a system of landscape classification based on dominant FGs and their recovery stages in the species-rich and structurally complex tropical landscape of a typical tropical forest region in South China. Our system of classification was based on remote sensing imagery, field grid sample plot investigation, and GIS analysis. The accuracy of the classification system revealed that this approach is feasible in the tropical forest landscape of Hainan Island in South China, and probably could be extended to other species-rich and structurally complex forest landscapes such as the tropical rainforest and subtropical evergreen broadleaved forest ecosystems in China and other regions of the world. Our results will help to develop effective management and restoration plans for key species and tropical forests.

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