Assessment of Tropical Forest Degradation with Canopy Fractional Cover from Landsat ETM+ and IKONOS Imagery

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ABSTRACT: Tropical forests are being subjected to a wide array of disturbances in addition to outright deforestation. Selective logging is one of the most common disturbances ongoing in the Amazon, which results in significant changes in forest structure and canopy integrity. Assessing forest canopy fractional cover (fc) is one way of measuring forest degradation caused by selective logging. In this study we applied a linear mixture model to a vegetation index domain to map canopy fractional cover in tropical forests in the Amazonian state of Mato Grosso, Brazil. The modified soil adjusted vegetation index (MSAVI) was selected as the optimal vegetation index in the model because it is most linearly related to green canopy abundance up to leaf area index = 4.0. In the canopy fc map derived from the Landsat Enhanced Thematic Mapper Plus (ETM+) image, the fc distribution ranged from 0 to 0.4 in clear-cut areas, higher than 0.8 in undisturbed forests, and a wider range of 0.3–1.0 in degraded forests. The fc map was validated with the 1-m panchromatic sharpened

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IKONOS image. In the logged forests the ETM+ estimated fc values were clustered along the 1:1 line in the scatterplot with the IKONOS estimated fc and had a squared correlation coefficient ($R^2$) of 0.8.

KEYWORDS: Forest degradation; Remote sensing; Selective logging

1. Introduction

The Brazilian Amazon rain forest has been subjected to various direct and indirect human impacts in the past decades. It has been deforested rapidly to establish agriculture and pasture activities (Skole et al. 1997). The clear-cut fragmented the remaining forests and exposed vast quantities of the resulting forest edges to greater amounts of drought and wind (Cochrane et al. 1999). In addition to deforestation, selective logging has become a dominant form of land use in the Amazon (Asner et al. 2004) and large forested areas of the Amazon region have been impoverished by this type of degradation at an approximate rate of 10 000–15 000 km$^2$ yr$^{-1}$ (Nepstad et al. 1999). The damage from selective logging operations often results in as many as 40% of the remaining trees being killed or severely injured (Uhl et al. 1991).

Selective logging leads to a variety of short- and long-lived effects including changes in forest microclimate, nutrient cycling, tree species composition, carbon release, and global climate (Pereira et al. 2002). The forest/nonforest classification with remote sensing imagery, which is a typical method in studies of deforestation and its effects on global carbon cycle and climate change (Laurance et al. 2001; Skole et al. 1997; Cochrane et al. 1999; Houghton et al. 2000), is not applicable in detecting selective logging. Although log patios are the most obvious damage areas on the ground and are visible in satellite imagery, they only account for a very small portion of the forest damage, which is primarily from logging roads, skids, and tree falls (Asner et al. 2002). Detecting the spatial extent of these damages is a challenging task in remote sensing communities. Asner et al. (Asner et al. 2002) and Pereira et al. (Pereira et al. 2002) compared two different types of selective logging (conventional and reduced-impact) with intensive multiyear ground measurements of gap fraction following logging activities. However, it is extremely difficult to visualize these differences by simply comparing spectral values in medium-resolution remotely sensed imagery as Landsat Enhanced Thematic Mapper Plus (ETM+; Asner et al. 2004). Although texture analysis is a common method to detect spatial variation in remotely sensed imagery, when the gap fraction is less than 50%, the forest openings cannot be successfully detected (Asner et al. 2004). A new measure is needed to quantitatively assess forest degradation by selective logging with remotely sensed imagery.

Canopy fractional cover (fc) can be one of the indicators of forest degradation. Remotely sensed data are ideal for assessing fc because of their capability to cover large areas. DeFries et al. (DeFries et al. 2000) defines global continuous fields of vegetation that separate one pixel in coarse-resolution imagery (>1 km) into percentage cover of several vegetation types. This concept can also be applied in degraded forests in which each pixel is composed of tree canopies and open area. During the dry season in the Amazon grasses and leaf litter in open areas are senescent and have similar spectral properties to soils. Therefore, the green tree canopy and open area have distinct spectral signatures in remotely sensed data.
The spectral response of the pixel in logged forests is thus the collective contribution of these two components. The canopy fractional cover is determined by the area of tree canopies in one pixel. Any satellite image with moderate to coarse resolution [such as Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), and Advanced Very High Resolution Radiometer (AVHRR)] can be used in this method.

Inferring subpixel information has been extensively studied with linear mixture models in the reflectance domain. Hanan and Prince (Hanan and Prince 1991) combined red and near-infrared (NIR) reflectance in an area-additive model to estimate the abundance of vegetation. Jasinski and Eagleson (Jasinski and Eagleson 1990) used a pixel’s distance to the soil line in the NIR–red reflectance scattergrams to estimate fractional vegetation cover. DeFries et al. (DeFries et al. 2000) estimate the percentage cover of each vegetation type in one pixel of coarse-resolution image. Lu et al. (Lu et al. 2003) use a linear mixture model to classify different secondary succession stages over logged areas. All the studies above apply the linear mixture model in several reflectance bands with a least square error optimization technique that needs intensive computation. It is thus very time consuming to apply the model with multiple Landsat images to assess the forest degradation in large areas in the Amazon region.

Another drawback of using linear mixture model in spectral domain is the internal and external effects to the reflectance. Although surface reflectance is primarily a function of the dominance of green vegetation, it also varies with moisture conditions and structures of both vegetation and soil. The influence of some external factors such as sun–target–sensor geometry is also inevitable (Townshend 1999). Vegetation indices, mostly the mathematical combinations of two or more spectral reflectances, can be used to suppress the spectral variations of reflectance (Jasinski 1990), and make the mixture model less sensitive to those factors (Gutman and Ignatov 1998; Qi et al. 2000). Vegetation indices have long assisted forest-cover studies. Lyon et al. (1998) analyzed Landsat scenes separated by 18 yr to detect land-cover changes in Mexico using the normalized difference vegetation index (NDVI). Young and Wang (Young and Wang 2001) also used NDVI to monitor vegetation productivity instead of land-cover types. Ellera et al. (Ellera et al. 1996) developed a fire index from NDVI to monitor the fire disturbance in forests.

NDVI has been used in linear mixture model to estimate fractional cover on low-density vegetated surfaces (Qi et al. 2000; Zeng et al. 2000); however, it is problematic when applied to tropical forests because of the rapid saturation with higher green biomass. In this study we applied a linear mixture model in the optimal vegetation index domain to derive tropical forest fractional cover and to study the capability to detect selective logging the study area. The canopy fractional cover maps derived from ETM+ imagery were validated with 1-m pansharpened IKONOS imagery to examine the validity of such approach for forest degradation assessment.

2. Study area and data description

The study area is in the Amazonian state of Mato Grosso, Brazil, covering one Landsat ETM+ scene (path 226, row 68). The major land-cover types are undis-
turbed forests, selectively logged forests, and clear-cut areas. The tree canopies in logged forests are thinner than the undisturbed forests. Depending on the succession stage, sparse shrubs and young trees may appear in the pastures developed over the clear-cut areas but are not our concern in this study.

One ETM+ scene was acquired on 18 June 2000 and was atmospherically corrected with MODTRAN4.0 to calculate surface reflectance in each band. A high-resolution IKONOS image was acquired on 13 June 2000, approximately 5 days earlier than the ETM+ image (Figure 1). It was assumed that there were no forest disturbances in the study area during these 5 days. The IKONOS image covers a subset of 7 km × 7 km in the study area. It was panchromatically sharpened to obtain a 1-m resolution multispectral data. Both tree canopies and openings can be visually identified at such resolution.

In the ETM+ and IKONOS composite color (NIR + red + green) images, forests are dark red and open areas are light blue (Figure 1). Since both acquisition dates were in the dry season, the open areas were senescent grass/shrubs and leaf litter with spectral response similar to soil. Over selectively logged areas, except for the logging roads and patios, the canopy cover variations due to selective logging cannot be detected visually on the 30-m ETM+ image. They can be seen, however, on the 1-m pan-sharpened IKONOS image, in which the canopy fraction gaps caused by logging are obvious. Because of its high resolution, the IKONOS image was used as ground truth to validate fractional cover maps derived with the ETM+ image when no field measurements are available.

3. Model development

3.1. Two-component linear mixture model

In a linear mixture model the reflectance of each pixel is assumed to be the sum of reflectance of all subpixel components, weighted by their percentage cover. These components are refereed as end members in this study. The equation can be written as (DeFries et al. 2000)

\[ R_i = \sum_{j=1}^{n} r_{ij}f_j + e_i, \] (1)

where \( R_i \) is the reflectance of one pixel in band \( i \), \( r_{ij} \) is the reflectance of end member \( j \) in band \( i \), and \( f_j \) is the percentage cover of end member \( j \) in such pixel. The term \( e_i \) is introduced to account for some insignificant remaining components within the pixel in this band.

In forest degradation studies, each pixel of the ETM+ imagery in the logged area is assumed to consist of two components: tree canopies and open areas. The mixture model then becomes a two-component linear model. The reflectances of these two components are independent of each other. Then Equation (1) can be written as

\[ R = R_{\text{canopy}}f_c + R_{\text{open}}(1 - f_c) + \varepsilon, \] (2)

where \( f_c \) is the tree canopy fractional cover in one pixel. Equation (2) suggests that the total spectral response of a pixel at certain wavelength is a linear combination

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Figure 1. Images (NIR + R + G) over the study area: (a) ETM+ image (18 Jun 2000), (b) subset of ETM+ image with the same area of IKONOS, and (c) IKONOS image (13 Jun 2000).
of responses from its tree canopy and open areas, weighted by the corresponding cover of each component, $f_c$ and $(1 - f_c)$, respectively. The reflectances of surface targets change significantly with wavelengths. Using different spectral bands may result in various fractional cover values (Maas 2000). Furthermore, even at certain wavelength, the values of $R_{\text{canopy}}$ and $R_{\text{open}}$ are highly influenced by the vegetation wetness, structure, soil moisture, texture, and external factors such as sun–target–sensor geometry (Townshend 1999). To reduce these problems, vegetation indices have been used in forest fractional cover estimation (Jasinski 1990; Gutman and Ignatov 1998; Zeng et al. 2000; Qi et al. 2000). For tropical forests in the study area, two-component assumption is close to reality, and therefore the error term $\varepsilon$ can be ignored. By using vegetation index (VI) as the proxy for all types of vegetation indices and replacing the spectral response $R$, Equation (2) becomes

$$\text{VI} = \text{VI}_{\text{canopy}} f_c + \text{VI}_{\text{open}} (1 - f_c),$$

where $\text{VI}_{\text{canopy}}$ is the vegetation index of tree canopy and $\text{VI}_{\text{open}}$ is the vegetation index of open areas. Then the canopy fractional cover ($f_c$) can be expressed as

$$f_c = \frac{\text{VI} - \text{VI}_{\text{open}}}{\text{VI}_{\text{canopy}} - \text{VI}_{\text{open}}},$$

where $\text{VI}_{\text{canopy}}$ and $\text{VI}_{\text{open}}$ are two end members empirically obtained from the ETM+ image using a statistical analysis. The common approach in choosing end members in a linear mixture model was to represent each end member with small homogenous areas in the image (Zeng et al. 2000). In this study the subregion of the homogenous full-cover forest and open areas were identified in the IKONOS image. The two end members in Equation (3), $\text{VI}_{\text{canopy}}$ and $\text{VI}_{\text{open}}$, were calculated as the mean in each subregion.

It should be noticed, however, that although both vegetation index and spectral reflectance are descriptions of vegetation properties, they are not linearly transformed. Equation (3) cannot be directly deducted from Equation (2). Instead it is an approximation by choosing the optimal vegetation index that is most linearly related with vegetation abundance in the study area.

### 3.2. Optimal vegetation index

The most commonly used vegetation indices include the normalized difference vegetation index (Tucker 1979); the soil adjusted vegetation index (SAVI; Huete 1988); the modified soil adjusted vegetation index (MSAVI; Qi et al. 1994); the enhanced vegetation index (EVI; Huete et al. 1999); the global environmental monitoring index (GEMI; Pinty and Verstraete 1992); and the Medium Resolution Imaging Spectrometer (MERIS) global vegetation index (MGVI; Gobron et al. 1999). Among these vegetation indices, NDVI is the earliest and most widely used vegetation index in remote sensing applications because of its simplicity. Most of the other vegetation indices are modified empirically from NDVI in an attempt to depress external effects and to improve the accuracy in extracting vegetation information from remotely sensed data.

To select an optimal vegetation index in the linear mixture model applied in tropical forests, all six vegetation indices mentioned above (NDVI, SAVI, MSAVI, EVI, GEMI, and MGVI) were calculated using reflectances simulated...
from the Scattering by Arbitrarily Inclined Leaves (SAIL) model (Verhoeft 1984) as a function of leaf area index (LAI). A forest of sparse to moderate density was modeled with LAI values from 0 to 4, which is similar to the degraded forest due to selective logging in the study area. The same sun–target–sensor geometry as Landsat satellite was used in the reflectance simulations. The dense undisturbed forest conditions were not considered because the LAI values were very high and all vegetation indices became saturated.

All vegetation indices increase with leaf area index (Figure 2). However, EVI, SAVI, and GEMI quickly saturate when LAI approaches 3.0. Although NDVI has a higher value and increases almost linearly at lower LAI, it saturates at a similar LAI value to the other three vegetation indices. MGVI has the highest value and does not saturate until LAI = 4.0, but the MGVI–LAI curve is a polynomial that increases rapidly when LAI is low then slows down when LAI is higher than 2.0. MSAVI has a more linear relationship with LAI and saturates only when the LAI is higher than 4. Since we are interested in an index that is most suitable for tropical forests with high vegetation abundance, MSAVI is the optimal vegetation index in this study.

MSAVI reduces the soil effect by adding a soil adjustment function determined by soil reflectance. Unlike the empirical factors in other vegetation indices, the adjustment factor in MSAVI changes as a function of canopy density and the slope of the soil line (Qi et al. 1994):

$$\text{MSAVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}} + L_0} (1 + L_0),$$

(5)
where $L_0$ is a soil adjustment factor and is expressed as a function of soil line slope and the reflectance properties of the targets

$$L_0 = [(\rho_{\text{NIR}} - \rho_{\text{red}})\text{slope} + 1 + \rho_{\text{NIR}} + \rho_{\text{red}}]^2 - 8.0\text{slope}(\rho_{\text{NIR}} - \rho_{\text{red}}). \quad (6)$$

The slope of soil line in this study area is 1.2, calculated from the surface reflectance at open areas in the ETM+ image. In the MSAVI image (Figure 3) the dense undisturbed forests have high values (light gray to white), the clear-cut areas have low values (dark gray or black), and the selectively logged areas along the logging roads and patios are in between (gray).

### 4. Results and analysis

Choosing MSAVI as the optical vegetation index in Equation (4), the fractional cover (fc) of each pixel in the ETM+ image was calculated. A $3 \times 3$ smoothing
window was performed to reduce the autocorrelation between adjacent pixels. The fc map derived from the ETM+ image was binned into 10 groups with an interval of 0.1 (Figure 4). All pixels with an fc value lower than 0.0 or higher than 1.0 were truncated into 0.0 or 1.0, respectively. The new clear-cut areas had low fc values (mostly 0–0.2). The pastures in late succession had fc values from 0.2 to 0.4 with the regrowth of young trees. The undisturbed forests had fc values of 0.8 to 1.0, indicating high canopy closure. The selectively logged forests have fc values between 0.6 and 1.0, whereas the fc around roads and logging patios are between 0.3 and 0.7 after the $3 \times 3$ window smoothing.

The fc map revealed forest degradation due to the selective logging activities in the study area. The extent of human activities was related directly to geographical accessibility in the tropical forests. Along the rivers and major roads in Figure 4 the lower canopy cover distribution revealed buffer zones in various widths, suggesting intensive selective logging activities. As an example of these disturbances a subset of ETM+ image and the estimated fc map was shown in Figure 5. On the ETM+ image (Figure 5a) the dense fish-bone features as a result of selective logging activities were obvious along the river tributaries and roads. On the cor-

![Figure 4. Canopy fractional cover map over the study area.](image)
Figure 5. Selective logging in the (a) ETM+ image and (b) canopy fractional cover map.
responding fc map (Figure 5b) the logging roads and patios range from 0.3 to 0.7 after smoothing. The extent of logging activities was mapped with fc ranging from 0.6 to 0.9 in the logged forests. At the bottom of the subset image there was a large area of intensively logged forests (grayish). Although the logging roads were obvious, the areas in the middle of the subset fc image only showed the isolated lines, indicating less intensive logging and the possible forest recovery. The bright reddish patterns in the ETM+ subset were forest regrowth in which the fc values were saturated (around 1.0) and cannot be identified in the fc map.

5. Validation with 1-m IKONOS image

The 1-m pan-sharpened IKONOS image covered a subset of the ETM+ image (Figure 1c). Over this subarea the major land-cover types were undisturbed primary forests, selectively logged forests, and clear-cut areas (Figure 6). The forested wetlands along the streams also were shown in the land-cover map but were excluded from the following analysis. Since the size of the tropical trees is much larger than 1 m, the pan-sharpened IKONOS image reveals enough details for the purpose of ground forest-cover mapping. With the lack of in situ field measurements in this study, the fc values estimated with the pan-sharpened IKONOS image were used as ground truth to validate the ETM+ estimated fc values.

An unsupervised classification technique was used to calculate fc in each 30 m × 30 m area in the IKONOS image. The IKONOS image was first classified into 30 clusters, and then their signatures were edited and merged into five classes: bright forest, dark forest, shaded forest, open area, and shaded open area. By merging the first three classes as forest (1) and the last two classes as open area (0), a forest/nonforest binary image was obtained. A 30 × 30 smoothing window was then applied to the binary image. After averaging, the resulting digital number was a float point value between 0 and 1, which is the fc value in each 30 m × 30 m area. These fc values from IKONOS image were used as ground truth to compare with the ETM+ derived fc values.

In the ETM+ and IKONOS-derived fc maps (Figure 7), both clear-cut (0–0.4) and undisturbed forested areas (0.8–1.0) are smooth and highly comparable. The examples of three land-cover types (clear-cut, undisturbed forest, and selectively logged forest) are also shown in the figure. In the selectively logged areas, the fish-bone texture shows up on both fc maps. The fc values in roads and logging patios varied between 0.3 and 0.7 in both fc maps as a result of 3 × 3 window averaging. In the ETM+ derived fc map, along the logging roads and patios, the buffer zones with lower fc values revealed the forest disturbances by logging activities. In the IKONOS-estimated fc map the buffer zones were much wider and almost covered the whole selectively logged forests (Figures 6 and 7b). One possible reason was that there were more shadows around the small open areas created by selective logging than in the undisturbed forests. As shown in the example of the selectively logged forest in Figure 7, these shadows can be easily detected and classified as open areas in the IKONOS image, but are not visible in the 30-m ETM+ image. Nevertheless, as shown in Figure 7a the ETM+ estimated canopy cover values in selectively logged forests ranged from 0.6 to 1.0, which revealed significant forest degradation as a result of selective logging activities.
In each of the three land-cover types (Figure 6) 300 locations were randomly selected and the fc values from ETM+ and IKONOS fc maps were compared in the scatterplot (Figure 8). The fc values of undisturbed forests are limited in the upper range of the scatterplot. The values in ETM+ fc saturate at 1.0, whereas the maximum in IKONOS fc is about 0.95 due to the inter-tree gap that is visible in the IKONOS image. In deforested areas the ETM+ fc values are between 0 and 0.4 resulting from clear cutting. Isolated young trees scattered around the area are not visible in a 30-m resolution of ETM+ image; however, they are visible in IKONOS image, which results in a much larger range of fc distribution (0–0.6). In the selectively logged forests the fc values from both images scatter along the 1:1 line,
indicating that the canopy cover reduction by logging activities can be detected from ETM+ image via linear mixture model. The total $R^2$ in the scatterplot covering all of the three land-cover types is as high as 0.91.

Since selective logging is the major concern in this study, we replot the ETM+ and IKONOS fc values in logged forests only (Figure 9a). Although the scatterplot shows a strong linear relationship, the regression line is highly skewed ($R^2 = 0.64$) because of the uneven statistical distribution of the 300 points in the fc range. As shown in the figure most of the fc values clustered at the high end of the plot while only isolated values locate at the low end. The high-end points represent undisturbed areas that compose a large portion in selectively logged forests. The low-end ones represent the logging roads and patios, which is only a very small portion of the logged forests (Asner et al. 2002). The points in the middle of the scatterplot are primarily from areas damaged by felled trees and skid trails.

To reduce the side effects of uneven distribution of sampling points in Figure 9a, we averaged fc values in both ETM+ and IKONOS with an interval of 0.01.
Although the interval is arbitrarily selected in this study, it is an averaging method commonly used when huge data points are involved (e.g., Pereira et al. 2002). The $R^2$ in the modified scatterplot is 0.8, which means that the ETM+ derived fc values fit the IKONOS-derived ones fairly well. In the undisturbed areas in the logged forests (ETM+ fc > 0.8) the two fc values are no longer linearly related because of the saturation of vegetation index in the ETM+ image.

6. Conclusions and discussion

In forest degradation assessment, forest canopy fractional cover is an obvious improvement over simple forest/nonforest classifications because of its potential in quantifying the extent and intensity of degradation. A linear mixture model in vegetation index domain was applied in this study to estimate the canopy fractional cover distribution using the Landsat ETM+ and IKONOS images. The MSAVI was selected as the optimal vegetation index because of its most linear relationship with green canopy abundance up to LAI = 4. The clear-cut areas have very low
Figure 9. Scatterplots of IKONOS- and ETM+ estimated fc values in selectively logged forests with (a) 300 sample points and (b) an average of these values in an interval of 0.01. The regression lines are also shown in both scatterplots.
fractional cover values (0–0.4) while in undisturbed forests the fractional cover tends to saturate. In selectively logged areas the fractional cover values range from 0.3 to 1.0, indicating various degrees of forest degradation. The forest fractional cover derived from the ETM+ image was validated with those from the 1-m panchromatic sharpened IKONOS image. A good correlation was found between the ETM+ and IKONOS-derived fc ($R^2 = 0.8$) while the latter was assumed to be ground truth.

In this study a modification to the linear mixture model is to use vegetation index instead of multiple reflectance bands. A great advantage of this modification is the reduced computation time, which is critical when many Landsat images are applied in basin-based studies of forest disturbances due to various human and natural activities. Although vegetation index is not a linear transformation of reflectance, the optimal vegetation index suitable for tropical forests minimizes the errors in the replacement.

The assumption of IKONOS image as ground truth could be problematic. The ETM+ derived fractional cover is primarily from green vegetation properties. At 1-m resolution, the IKONOS fc may be higher than the ETM+ fc because of the contribution of nongreen canopy components such as branches and trunks. It could also be lower because of some minor in-tree gaps and shadows that are visible in the IKONOS but neglected in the ETM+ image. The ideal way is to acquire ground-measured fractional cover values for the purpose of validation. However, by now the ground measurements of gap openings are primarily based on LAI-2000 or fisheye photos taken under forest canopy. In both methods the nongreen vegetation plays a large role, which results in higher fc readings. Acquiring “real” ground truth is still challenging in forest degradation studies with remote sensing imagery.

The mixture model is semiempirical. The fc values derived from the ETM+ imagery may vary depending on the values of the two end members ($V_{\text{canopy}}$ and $V_{\text{open}}$) in the model. In some forests, the assumption of only two components may not be valid when a third or fourth major land-cover component (such as water, healthy grass, or agricultural crops) in one pixel is common. In this case a multicomponent linear or nonlinear mixture model should be applied. A detailed forest-type map may be needed to apply the model in each forest type. The mixture model is best applied in dry season in the Amazon basin when the understory canopy (grass and shrub) turns to be senescent and has significant different reflecting properties from tree canopy. Otherwise, the high vegetation index from grasses and shrub leaves may result in high forest fractional cover values even if the tree canopy cover is very low.

The approach described in this study has a great potential for evaluating forest degradation as well as forest recovery when using multiple images at an annual basis. The fractional cover map shows the dynamics of canopy cover in tropical forests that have been subjected to human disturbances and natural processes. Since fractional cover is a quantitative measure of forest distribution, it may be used to assess the carbon sequestration in global change studies as a result of deforestation, forest degradation, and regrowth.

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