CHARACTERIZING TEMPORAL VEGETATION DYNAMICS OF WAVELET-FILTERED MODIS EVI TO DETECT LAND USE CHANGE IN JAVA ISLAND

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ABSTRACT: This paper explores the spatial and temporal complexity of land use change considering the land cover dynamics. Our research hypothesis is that consistent land use has a typical, distinct and repeated temporal pattern of vegetation index inter-annually and a change of that temporal pattern could be assigned as a change of land use. We analysed the dynamics pattern of long-term image data of wavelet-filtered MODIS EVI from 2001 to 2007. The change of dynamics pattern was detected by differentiating distance between two successive annual patterns, which then indicates a land use change. Moreover, we determined the type of changes by performing the pattern clustering method, and then were validated by ground check points and statistics data sets. The land use change that was detected by the change of temporal pattern, can be categorized into: 1) agricultural development (including some change trajectories such as: mixed garden changed to intensive agricultural cropping and developing a paddy field in mangrove), 2) urban development (e.g. mixed garden or upland converted into built-up), 3) deforestation (either naturally or man-made changes), 4) changes in mangrove area and 5) considering the plantation management (such as changes in plantation commodity). Meanwhile, a temporary change of land surface, which could be also understood by this study, explained that the climate regime was an important factor affected the temporal vegetation dynamics of land use types, especially agriculture land, such as paddy rice field, upland and plantation. For example, many agricultural lands became a barren land, cropping system was changed and the planting time was postponed caused by the extreme dry season which influenced by ENSO in July-September 2006.

1. INTRODUCTION

Land use change reflects human activities and environmental processes over time and over space which directly affect its status and impacts on goods and services (Verburg *et al.,* 2009). Information on land use change is a key input to a wide range of regional and global environmental issues, including land degradation, loss of biodiversity, climate change, food security, human vulnerability and environmental sustainability (Olson *et al*., 2004). Characterizing land use change in a systematic and harmonized way allows evaluating the various aspects of those environmental issues, particularly when information on related ecosystem characteristics and socio-economic attributes of the area are associated with it (Nachtergaele and Petri, 2008). Many efforts being undertaken to generate information on land use change, through field surveys, projects and local efforts, nevertheless, datasets of sufficient scope on land use change are generally scarce or outdated, particularly in some developing countries (George and Nachtergaele, 2002).

Advances in remote sensing technology enable land scientists make an assessment of current land resources and identifying an on-going land cover change processes and its locations (Herold *et al.,* 2006). Meanwhile, land use is not always observable, particularly in agricultural land use, when land use is systematically linked through temporal interactions, e.g. cropping system or crop rotations (Verburg *et al.,* 2009). Many land uses can be associated with a single land cover type; also, a single land use can be associated with many types of land cover. The previous study mentioned that characterization of dynamics pattern of land cover would provide sufficient, significant and useful information regarding the patterns of land use; and consequently it should be possible to consider the inter-annual land use change (Setiawan *et al.,* 2011). In addition, characterization of land surface reveals patterns of seasonal and inter-annual variations in land surface attributes that are driven not only by land use change, but rather by climatic variability or land management of the surfaces (Lambin *et al.*, 2003).

The purpose of study was to investigate a land use change based on characterizing temporal vegetation dynamics of land use. Our approach considers a seasonal events and climatic variability in land surfaces; consequently it should be possible to consider the actual land use changes.

2. METHODS

2.1. Data

The MODIS product used in this study is the MODIS EVI which is embedded in the MOD13Q1 product. The MOD13Q1 product is the Vegetation Indices (VI) Composite 16-day Global 250 m SIN Grid V005, and the MODIS Land Discipline Group has developed an algorithm of EVI for use with MODIS data (MODLAND, 2010). It is computed by algebraic combination of three spectral bands (red, blue and NIR) and designed to enhance the contribution of vegetation properties (Huete *et al.*, 1997).

Improving aerosol correction at the surface reflectance level (MOD09) and a new filtering scheme in the VI algorithm implemented in collection 5.0 has positively impacted the MODIS VI (Didan and Huete, 2006). Moreover, to get a greater percentage of clear-sky data, the maximum value composited (MVC) method is applied to the MODIS VI and is combined with the MODIS BRDF (bidirectional reflectance distribution function) or MOD43 product to generate the 16-day composite MODIS VI (MOD13Q1 product) (Huete *et al.*, 1999). Nevertheless, if the composite period is too long, the land surface does not remain static; and if it is too short, the atmospheric disturbance cannot be removed effectively (Lu *et al.,* 2007); consequently, there are some residual errors. Such noise degrades the data quality and introduces considerable uncertainty in temporal sequences, confusing the analysis of temporal images sequences by introducing significant variations in the EVI time series data. Therefore, noise reduction or fitting a model to observe data is necessary before analysis of vegetation dynamics can be determined.

In this study, we used the MODIS EVI datasets which has been filtered by wavelet transforms for reducing the residual noise of image data (Setiawan *et al.*, 2011). The MODIS EVI datasets were acquired from January 2001 to December 2007 and captured 161 time series with the interval time 16 days. Then, to examine the details of the temporal pattern of the MODIS EVI and analyse the change of it, we used a finer spatial resolution Landsat TM and ETM+, a high resolution image (Google Earth) as well as reference data derived from the ground survey points.

2.2. Image transformation using wavelet function

The wavelet transform decomposes a signal into different scales by successively translating and convolving the elements of a high-pass and low-pass scaling filter associated with the mother wavelet. We used the *coiflet* mother wavelet because this wavelet shape is as similar as possible to the temporal vegetation dynamics of a crop phenology as pointed out by Sakamoto *et al*. (2005).

In this processing, the order 2 of *coiflet* function was used since the trend of that order is similar to the trend of the original data. Order of the wavelet function is a measure of the wavelet's smoothness, where a higher order produces a smoother wavelet. This analysis was performed using MATLAB through the 1-D multisignal wavelet analysis function. The MODIS EVI data pre-processing was conducted to provide a filtered data set to support multi-temporal analysis.

The result of filtering pattern of one pixel and image transformation by using wavelet function is given in Figure 1 and 2, respectively. Figure 1 show that wavelet transform filters some noises (de-noise) of MODIS EVI time-series data; so that the planting, heading and harvesting dates in the agricultural land especially can be determined.

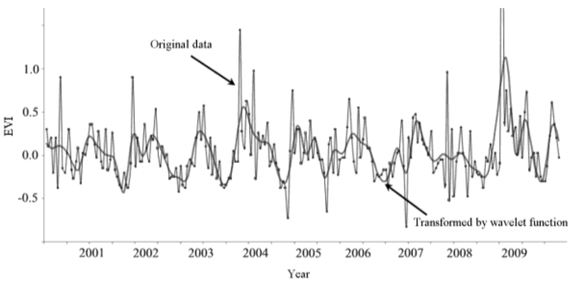

Figure 1. Filtering pattern of one pixel MODIS EVI by wavelet function

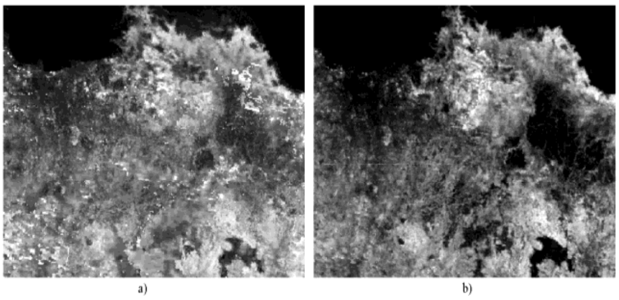

Figure 2 a) image before transform, and b) image after transform

2.3. Change Analysis of Successive Patterns

Land use change analysis based on the comparison of different dates independently does not allow recognizing the temporary and permanent change within land use types. Therefore, land use change detection discussed here is performed through detecting a change of the temporal pattern of vegetation index of the successive years. The change area is assigned while a significant difference of the distance of EVI reached between each annual pattern (Figure 3, example for change in period 2006-2007).

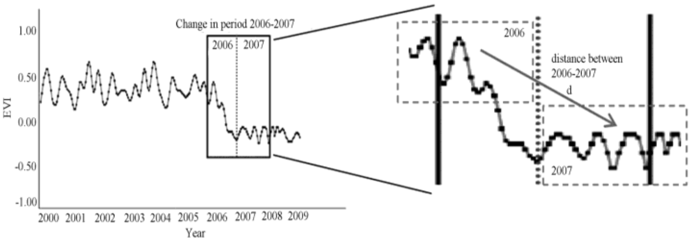

Figure 3. Illustration of change detection approach by the distance between successive patterns

Distance of EVI values of two successive years were computed for all grid cells included all consecutive study years (i.e. 2001-2002, 2002-2003, 2003-2004, 2004-2005, 2005-2006 and 2006-2007). The difference of distance of EVI value for those six change periods exhibited an approximately normal distribution about the mean (μ= 0), which, for this application, represented no change in EVI value between T_1 and T_2. Standard normal distribution statistical analysis was performed to identify cells that had the greatest change in distance of EVI value for each change period. Three change thresholds were selected corresponding to a range of *z-score* probabilities, that is: 2.0, 3.0, and 3.5. This range of values were selected because they produced appropriate estimates of annual change values based on previous change rate studies for the study area (Setiawan and Yoshino, 2011).

This study used an assumption that locations displaying similar significant changes of temporal patterns are inferred to have a similar type of land use change. The types of land use change are, in turn inferred to have relatively homogeneous change characteristics such as change in vegetation fractions and cover types. Distinguishing among those temporal patterns in order to recognize the type of land use change was accomplished using the *k*-mean clustering method based on Euclidean distance in an EVI-space in which each EVI image provides one dimension of the cluster space, analogous to spectral clustering. The clustering method subdivides datasets into k clusters through an iterative process in order to optimize a criterion function (Jain *et al.* 1999). Clustering yields a number of significant change patterns which correspond to 25 specific land use classes of the previous study (Setiawan *et al*., 2011).

3. RESULTS AND DISCUSSIONS

3.1. Threshold probability of change pattern

Standard normal distribution of statistical analysis was performed to identify the greatest changing of the distance of EVI value for each change period. The change detection results for the three change thresholds; that are threshold (TH) of factors 2.0, 3.0, and 3.5, for each change period, are summarized in Table 1. The TH factors of 3.5 provided the best accuracy at 82.99%, meanwhile TH of 2.0 and TH of 3.0 are 77.98% and 80.53%, respectively. The TH of 3.5 was statistically significant at level 95% (α:0.05) compared to the TH factors of 2.0 for the change period of 2004-2005 (p: 0.005) and 2006-2007 (p: 0.023); however, it was not significantly different from TH factors of 3.0. Alternatively, in application of a change detection, the TH of 3.0 could be applied as a threshold since it was also statistically significant compared to the TH of 2.0 for the three change periods, 2002-2003 (p:0.04), 2004-2005 (p:0.016) and 2006-2007 (p:0.003).

3.2. Change pattern identification

This study assumes that locations displaying similar significant change of EVI profile are inferred to have a similar type of land use change. Accordingly, the pathway of change, which distinguished by clustering method, could be defined as a type of land use change. We made the distinction of the significant change patterns into 25 patterns per period or totally 150 patterns for six periods to first provide a segmentation of significant change pattern (Figure 4). The identification of those patterns have been performed using a corresponding ground survey data set, local knowledge and other image data such as Landsat TM/ETM as a reference. The results of change pattern identification, e.g. period 2001-2002, are given in Table 2. Figure 4 and Table 2 indicate that one typical type of land use change might be identified from more than one change patterns, e.g. a change area in industrial forest plantation (converted into an intensive agricultural land/upland) was defined from 3 types of change patterns. Moreover, our results also indicate that a change pattern does not always indicate a change of land use, particularly in agricultural land use type, since there is a complexity caused by the seasonal variability and land use management (activities). That complexity of land use change detection is discussed in the following section.

Table 1. The change detection results for the three change thresholds

(a) Accuracy assessment of three change thresholds

	TH-2						
Land use type	**2001-2002**	**2002-2003**	**2003-2004**	**2004-2005**	**2005-2006**	**2006-2007**	**AVERAGE**
Natural Forest	80.4%	89.1%	86.7%	58.5%	86.2%	61.5%	77.1%
Bush	64.0%	61.8%	54.9%	46.1%	69.1%	59.3%	59.2%
Mangrove	66.7%	91.7%	85.7%	89.4%	87.1%	91.7%	85.4%
Industrial forest plantation	73.2%	59.3%	70.7%	60.2%	61.7%	66.7%	65.3%
Plantation	88.9%	100.0%	63.2%	96.0%	83.6%	95.7%	87.9%
Paddy rice field	98.2%	70.4%	90.9%	91.7%	96.6%	92.9%	90.1%
Mixed garden	80.7%	75.6%	84.6%	85.7%	80.2%	83.0%	81.6%
Upland	86.7%	64.3%	62.1%	59.3%	60.3%	51.9%	64.1%
Builtup	97.7%	94.8%	91.9%	95.7%	89.5%	88.0%	92.9%
Fish/shrimp pond	82.9%	89.4%	89.3%	84.0%	91.4%	98.4%	89.2%
Water	66.7%	48.7%	100.0%	44.2%	81.8%	48.8%	65.0%
AVERAGE	**80.5%**	**76.8%**	**80.0%**	**73.7%**	**80.7%**	**76.2%**	**78.0%**

	TH-3						
Land use type	**2001-2002**	**2002-2003**	**2003-2004**	**2004-2005**	**2005-2006**	**2006-2007**	**AVERAGE**
Natural Forest	80.4%	75.0%	70.6%	63.6%	75.0%	66.1%	71.8%
Bush	61.8%	68.3%	56.1%	53.8%	66.9%	85.5%	65.4%
Mangrove	62.5%	79.2%	87.8%	86.1%	81.5%	91.1%	81.4%
Industrial forest plantation	74.6%	74.4%	79.8%	65.9%	77.3%	87.2%	76.5%
Plantation	94.2%	98.4%	85.2%	62.6%	95.3%	93.0%	88.1%
Paddy rice field	98.2%	84.8%	92.1%	94.9%	96.2%	95.2%	93.6%
Mixed garden	78.1%	84.5%	91.8%	81.9%	86.5%	86.3%	84.9%
Upland	88.0%	71.0%	67.0%	72.3%	69.7%	71.6%	73.3%
Builtup	96.9%	93.2%	87.9%	93.8%	86.5%	84.6%	90.5%
Fish/shrimp pond	76.6%	84.9%	86.7%	77.7%	87.2%	97.1%	85.0%
Water	88.2%	63.4%	58.8%	74.4%	94.2%	73.0%	75.4%
AVERAGE	**81.8%**	**79.7%**	**78.5%**	**75.2%**	**83.3%**	**84.6%**	**80.5%**

	TH-4						
Land use type	**2001-2002**	**2002-2003**	**2003-2004**	**2004-2005**	**2005-2006**	**2006-2007**	
Natural Forest	97.4%	96.3%	97.1%	81.9%	95.1%	88.5%	92.7%
Bush	66.7%	71.4%	48.8%	56.9%	70.4%	69.9%	64.0%
Mangrove	83.3%	92.9%	100.0%	91.2%	91.4%	94.6%	92.2%
Industrial forest plantation	77.8%	69.6%	71.4%	72.8%	73.6%	79.5%	74.1%
Plantation	90.9%	100.0%	83.3%	92.1%	94.4%	91.2%	92.0%
Paddy rice field	96.2%	88.2%	89.5%	94.8%	96.9%	95.6%	93.5%
Mixed garden	79.3%	89.2%	93.3%	77.4%	79.5%	76.5%	82.5%
Upland	85.8%	75.6%	83.0%	73.5%	68.5%	64.6%	75.2%
Builtup	95.5%	90.2%	85.0%	91.8%	81.3%	78.6%	87.1%
Fish/shrimp pond	77.8%	85.0%	92.3%	77.3%	88.9%	95.8%	86.2%
Water	84.6%	69.7%	63.2%	68.1%	92.6%	62.2%	73.4%
AVERAGE	**85.0%**	**84.4%**	**82.4%**	**79.8%**	**84.8%**	**81.5%**	**83.0%**

(b) Comparison of three change thresholds by independent sample test

Independent sample Test	Period	Test for Equality of Variances		t-test for Equality of Means	
		F	Sig	t	df
TH-2 Vs TH-3	2001-2002	0.0950	0.7611	-0.2355	20
	2002-2003	4.8079	**0.0403**	-0.4821	20
	2003-2004	0.2628	0.6138	0.2449	20
	2004-2005	6.9691	**0.0157**	-0.2060	20
	2005-2006	0.1396	0.7126	-0.5516	20
	2006-2007	11.9100	**0.0025**	-1.3132	20
TH-3 Vs TH-3.5	2001-2002	1.2886	0.2697	-0.6817	20
	2002-2003	0.1031	0.7515	-1.0056	20
	2003-2004	0.0161	0.9003	-0.6357	20
	2004-2005	0.1271	0.7252	-0.8568	20
	2005-2006	0.1783	0.6774	-0.3398	20
	2006-2007	1.1718	0.2919	0.6336	20
TH-2 Vs TH-3.5	2001-2002	0.6098	0.4440	-0.9737	20
	2002-2003	4.0249	0.0585	-1.2352	20
	2003-2004	0.0704	0.7935	-0.3792	20
	2004-2005	10.1500	**0.0046**	-0.8646	20
	2005-2006	0.0029	0.9574	-0.8539	20
	2006-2007	6.0908	**0.0227**	-0.7911	20

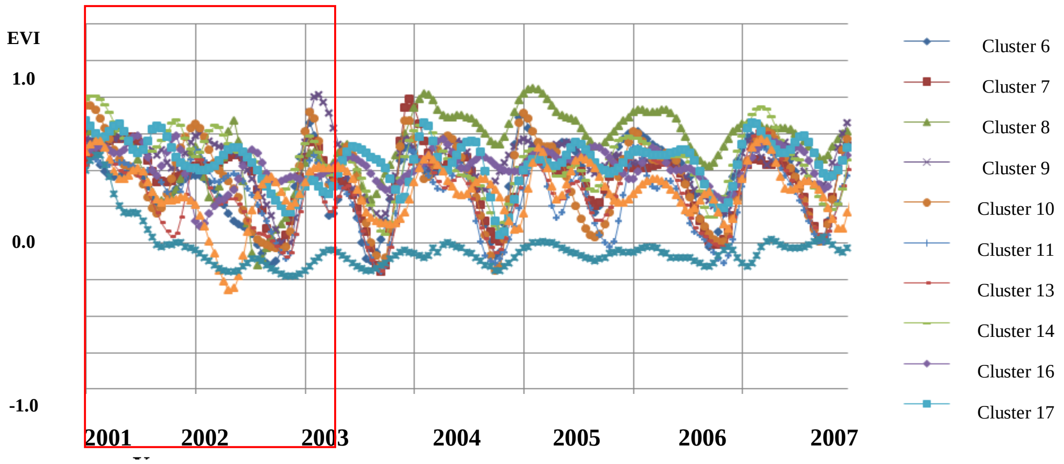

Figure 4. The result of clustering process which assigned as a land use change in period 2001-2002

Table 2. The result of change pattern identification for period 2001-2002

Cluster	The pathway of change
6	Industrial forest plantation converted to barren land (harvesting), hereafter changed to intensive upland (community-based forest management/PHBM)
7	Industrial forest plantation converted to barren land (harvesting), hereafter changed to intensive upland (community-based forest management/PHBM)
8	Upland mixed converted to barren land, then develop to be a plantation
9	Mixed garden changed to barren land, then planted by upland crops
10	Upland mixed garden changed to barren land, then develop to be an intensive upland
11	Mixed garden changed to barren land, then develop to be an intensive upland
13	Industrial forest plantation converted to barren land (harvesting), hereafter changed to intensive upland (community-based forest management/PHBM)
14	Commodity change in plantation area (after harvesting), as a portion of management practices
16	Forest mixed bush converted to barren land by burned, then planted by upland crops mixed bush
17	Bush/shrub converted to barren land and upland
19	Bush/shrub changed to barren land by burned, then planted by upland crops intensively
22	Mixed garden-bush converted to built-up (settlement)

3.3. Land use change and accuracy assessment

The use of temporal vegetation patterns allowed land use change to be differentiated from the temporarily change of land surface. Moreover, some attributes of land use change such as a location, area, time and mechanism of the change could be obtained. The distribution of land use change detected by the approach is shown in Figure 5

Performance of our change detection approach was evaluated by 21,357 reference pixels, which revealed the overall accuracy to be 76.10%. Comparing accuracy among the change in several land use types reveals a variation of its accuracy. The greatest error of the approach was associated with the bush, upland and industrial forest plantation classes. Specifically, 64.09% of bush, 91.88% of industrial forest plantation and 70.30% of upland were assigned to a change area; even those areas have not been changed actually. Meanwhile, a change in non-vegetated land use types including built-up (settlement, mining and open-area), fishpond and water are not examined, because of the reference data of those classes are unacceptable in change category. The paddy rice field had the greatest overall accuracy (94.02%), followed mangrove (87.57%), plantation (86.62%), mixed garden (82.55%), and natural forest (81.97%). In the natural forest and mangrove cases, 44.61% and 38.67% of the error, respectively, is due to omission error, meaning that the change area in those classes was assigned incorrectly. The results show that the change in plantation, paddy rice field and mixed garden could be detected more accurate relatively than other classes. In detail, the change area in plantation, mixed garden and paddy rice field were 76.92%, 69.40% and 66.32%, respectively assigned correctly as a land use change.

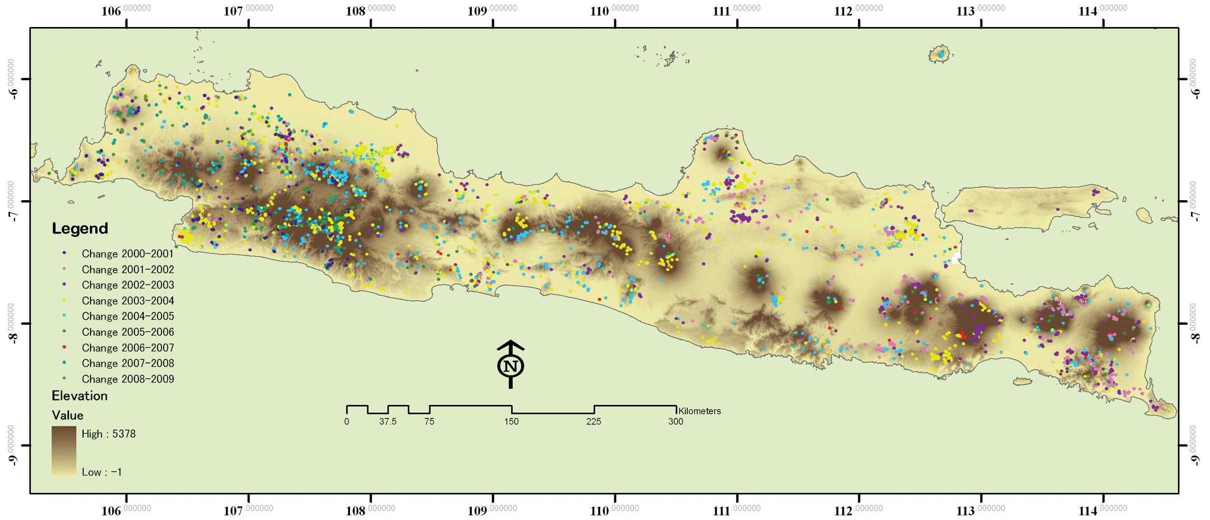

Figure 5. Distribution of land use change in Java Island, Indonesia, which can be detected by temporal pattern

The land use change that was detected by the change of temporal pattern, can be categorized into: 1) agricultural development (including some change trajectories such as: mixed garden changed to intensive agricultural cropping and developing a paddy field in mangrove), 2) urban development (e.g. mixed garden or upland converted into built-up), 3) deforestation (either naturally or man-made changes), 4) changes in mangrove area and 5) considering the plantation management (such as changes in plantation commodity).

4. CONCLUSION

This study is based on the hypothesis that a pixel representing a change area while the inter-annual temporal dynamics of land surface is changed. The land use change could be identified from a long time series data of land cover, since the land use has a typical, distinct and repeated temporal pattern of vegetation index inter-annually. We examined the temporal vegetation dynamics of land use by applying the wavelet-filtered MODIS EVI images from 2001 to 2007 in order to investigate the land use change.

The temporal pattern analysis of the MODIS EVI has a significant advantage for both capturing the actual timing of the change event and monitoring of the vegetation growth. However, such capabilities are limited by spatial resolution of the data. The use of multi-temporal data sets was necessary to develop methodologies that utilize information on inter-annual variations to increase the accuracy of the land use change analysis.

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