DETECTING AND MODELLING DYNAMIC LANDUSE CHANGE USING MULTITEMPORAL AND MULTI-SENSOR IMAGERY

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ABSTRACT:

It is now common to use data from two or more sensors for land cover change detection. Since the spatial and spectral resolutions of different sensors vary significantly, the ability to discriminate the land cover also varies greatly. In this paper the applications of landuse change detection including area statistics, temporal trajectories and spatial pattern are discussed. The area statistics show the general landuse change pattern, but with quite significant uncertainty. The results of this study show that if the area of detected landuse change accounts for less than 5% of the total area, the uncertainty of change detection can be very significant. Temporal trajectory analysis was also conducted with the particular focus on the analysis of unchanged and "stable" change trajectories, because they generally show the trend of landuse change that is irreversible. Unstable change trajectories, on the other hand, show relatively less significance since they largely contain reversible temporary changes (e.g. seasonal cropping and bare ground) and classification errors. The study results show overall accuracy of 85-90% with Kappa coefficients of 0.66-0.78 in classification and change detection. On spatial patterns, the landuse pattern metrics demonstrate a reasonable result, but most other patch metrics do not show recognisable patterns.

1. INTRODUCTION

Land cover change plays a pivotal role in regional socio-economic development and global environment changes (Chen 2002). In arid environment, where fragile ecosystems are dominant, the land cover change often reflects the most significant impact on the environment due to excessive human activities.

When monitoring natural environment and land cover change, three aspects are focused (Singh 1989, MacLeod and Congalton 1998):

- areal extent of the change, measuring the magnitude of the change;
- the nature of the change, measuring the temporal trajectory of the change;
- spatial pattern of the change, measuring spatial distribution and relationship of the change.

Numerous works have been reported in these fields (Miller *et al* 1998, Mertens and Lambin 2000, Petit *et al* 2001, Maldonado *et al* 2002, Pereira *et al* 2002). For landuse change detection, imagery data from various sensors such as Landsat MSS, TM, ETM, SPOT HRV, IRS and AVIRIS are often used, and it is common that images from two or more sensors were used (Prakash and Gupta 1998, Luque 2000, Masek *et al* 2000, Mertens and Lambin 2000, Roy and Tomar 2001, Ustin and Xiao 2001, Yang and Lo 2002). Since the spatial and spectral resolutions of different sensors vary significantly, the ability to discriminate the land cover also varies greatly. Some research work has been reported on the effect of multi-resolution sensors on spatial pattern metrics statistics based on the same stage multi-resolution imagery (Benson and MacKenzie 1995, Wickham and Riitters 1995), in which the focus of discussion was on the effects of spatial resolution on the landscape spatial pattern metric using multi-resolution remotely sensed imagery with the same acquisition period. Less attention, however, was paid to the effect of multi-resolution and multitemporal data on area statistics, trajectory statistics and spatial pattern metrics. This study evaluates the effect of multi-resolution data on the change detection in an arid environment over a monitoring timeframe of 30 years. The focus of the discussion is on the statistics of area extent, temporal trajectories and spatial pattern.

2. METHODOLOGY

The generic approach of this study is based on post-classification comparison method, which is commonly employed in land cover change detection studies (Miller *et al* 1998, Larsson 2002, Yang and Lo 2002, Zhang *et al* 2002, Liu and Zhou 2004). A unified land cover classification scheme was established for classification of images. The classified images were then used to derive class area statistics, temporal trajectories and spatial pattern in the past 30 years.

2.1 Study area and data

The study area is centred at 41°5'N and 85°43'E and located in Donghetan Township, Yuli County, Xinjiang Uygur Autonomous Region, China. It locates at the middle reach of Tarim River, the longest inland river of China (figure 1). At the fringe of Taklimakan Desert, the "green corridor" of Tarim Basin is one of the most important habitation areas in aridzone

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of China. The landscape in Donghetan is typical in Tarim River Valley, with a generally dry and harsh environment, represented by typical desert vegetation and soils. With the increasing land development in recent decades, the fragile environment has experienced quite remarkable change, largely reflecting the general development trend and temporal effect of government policies and administrative measures.

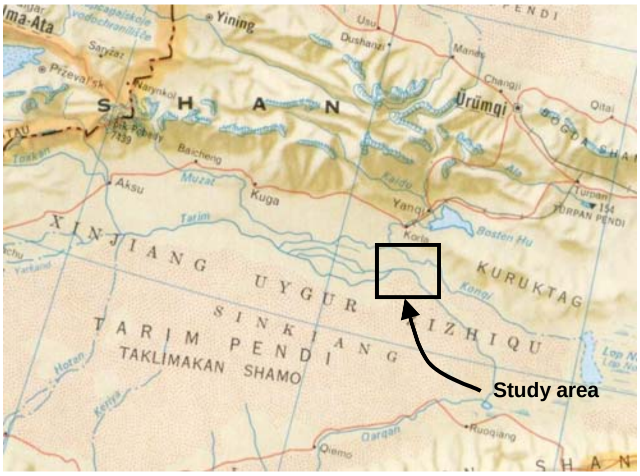

Figure 1. Location map of the study area.

Five multi-temporal remotely sensed images were acquired for change detection of this study (table 1), including Landsat MSS, TM, ETM and SPOT HRV multispectral images. In addition, a multispectral 4-m resolution IKONOS image was acquired in September 2000 for field investigation and accuracy assessment of image classification. The images were geometrically rectified and registered on the map coordinates (table 2).

Table 1. Data used in this research.

Satellite	Sensor	Path/Row	Resolution (m)	Acquisition Date
Landsat 1	MSS	154/31	57*	3/7/1973
Landsat 2	MSS	154/31	57*	12/10/1976
SPOT 1	HRV	216/266/9	20	20/7/1986
Landsat 5	TM	143/31	30	25/9/1994
Landsat 7	ETM	143/31	30	17/9/2000

* Resampled resolution.

Table 2. RMS errors on geometric correction and registration of the images.

	RMSE X (pixels)	RMSE X (m)	RMSE Y (pixels)	RMSE Y (m)
MSS (1973)	0.23	13.11	0.35	19.95
MSS (1976)	0.38	21.66	0.49	27.93
SPOT (1986)	0.21	4.20	0.22	4.40
TM (1994)	0.24	7.20	0.20	6.00
ETM (2000)	0.17	4.85	0.16	4.56

2.2 Classification and accuracy assessment

Using the unified land cover classification scheme developed in a previous study (Zhou *et al* 2004), the multitemporal images were classified into five classes including 'grass and woodland', 'salty grass', 'water body', 'bare ground' and 'cropland'. The classification accuracy was assessed using the common 'confusion matrix' method, showing an overall accuracy of 85-90% with a Kappa coefficient of 0.66-0.78. The details were reported by Zhou *et al* 2004.

2.3 Change detection

2.3.1 Measuring the area extent of the change: The five-date classified images were integrated to GIS database. The area statistics of land use classes were obtained from attribute tables.

2.3.2 Establishing landuse change trajectories: Based on the classification scheme, all possible landuse change trajectories are shown in figure 2. Note that there was no cropland found in this area before 1990's so that the class "C" is not included in the classification of 1973, 1976 and 1986 images. As highlighted in figure 2, for example, a trajectory can be specified as G → W → G → G → C, meaning that the land was found as grass/woodland in 1973, water body (flooded) in 1976, grass/woodland again in 1986 and 1994, and cultivated as cropland in 2000.

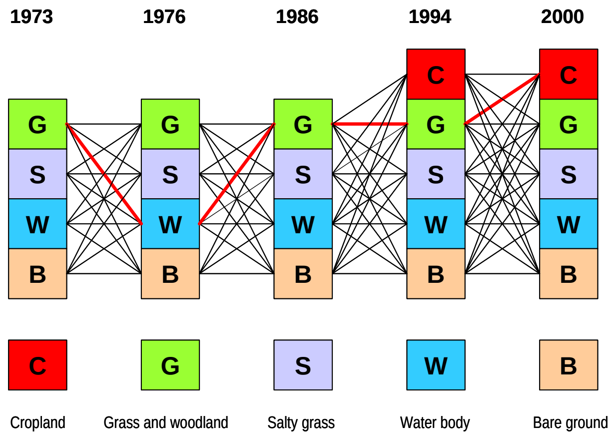

Figure 2. All possible landuse change trajectory identified for the study area.

For the analysis of temporal human impact on the environment, we have classified all found trajectories into three generic classes, namely, unchanged, stable change and unstable changes (table 3). The <u>unchanged</u> class includes trajectories such as G → G → G → G → G and W → W → W → W → W indicating that the same land cover type was found on the sample point over the past 30 years. The <u>stable</u> change class includes decisive changes due to human activities such as building dam/reservoir and cultivation. They represent the major human impact on the environment. The representative trajectories of this class include, e.g., G → G → G → C → C, S → S → G → G → C, and G → G → W → W → W. The <u>unstable</u> change class includes those indecisive changes due to the natural processes or minor human activities such as light grazing. For example, grassland may be flooded during summer and subsequently dried out as salty grass because of strong evapotranspiration. Examples of trajectories of this class are G → W → B → G → G (flooded, eroded and recovered) and G → W → G → W → G (repeatedly flooded).

The accuracy of the trajectories was assessed using the percentage of the 'true' landuse trajectories. If at a sample point, the landuse classes were all confirmed by the five-date ground references, the case was regarded as 'true' trajectory, otherwise it is a 'false' case. We have chosen a stratified random sampling scheme for selecting sample points of reference data for trajectory accuracy assessment. 790 sample points were generated using the method as reported by Zhou *et al* (2004).

Table 3. Classification of landuse change trajectories.

Level 1 classes	*Level 2 classes*	*Description*	*Trajectory examples*
Unchanged	Grass/wood land	No change	G→G→G→G →G
	Salty grass	No change	S→S→S→S→ S
	Water body	No change	W→W→W→W →W
	Bare ground	No change	B→B→B→B→ B
Stable	Old cultivation	Changed to and remained as cropland since 1994	G→G→G→C→ C
	New cultivation	Changed to and remained as cropland since 2000	S→S→G→G→ C
	Abandoned cultivation	Revered from cropland to other classes in 2000	G→G→G→C→ G
	Reservoirs/ponds	Changed to and remained as water bodies since 1986	G→G→W→W →W
Unstable	Grass/woodland	Periodical changes between cover G and S	G→S→G→G→ S
	Flooded	Periodical changes between cover W and other types	G→W→G→W →G
	Bare ground	Periodical changes between cover B and other types	G→B→B→G→ B

2.3.3 Analysing spatial pattern: The spatial pattern of landuse influences the ecological process of movement of matter and energy. The spatial pattern of landuse and land cover has been actively researched in the field of landscape ecology (Miller *et al* 1998, Farina 1998). In this study we have selected five variables to analyze landuse patch characteristics and landscape patterns. Table 4 summarizes the computation and interpretation of these variables.

Spatial pattern is different from the area statistics and temporal trajectories because the effect of errors cannot be detected from ground references and their corresponding statistics directly. Generally, landuse pattern parameters should reflect the overall trend of landuse change, so that they should not show acute fluctuation over long time series. We therefore propose to use the time series to assess the effect of multi-resolution imagery.

1. If the change of metrics for every landuse class from one time to another is stable, the metrics are comparable and can reflect the regularity of land use spatial pattern change. These metrics can be regarded as a metrics that can be used and are not affected by resolution of remote sensing data.
2. If the change of metrics for every land use class from one time to another is not stable, and obviously related to the spatial resolution of the data, these metrics are regarded as being affected by the spatial resolution of data and they can be used with care.
3. If the change of metrics from one time to another is not stable, and, though related to the spatial resolution obviously, the metrics for the same spatial resolution are not comparable, the metrics cannot be used.

Table 4. Spatial statistics for analyzing spatial patterns of landuse changes.

Abbreviation	*Name*	*Equation**	*Interpretation*
PPU (Frohn 1998)	Patch Per Unit	$PPU = \frac{m}{A}$	Fragmentation of area pattern, with higher values indicating more fragmented areas.
PAFD (Saura and Martínez-Millán 2001)	Perimeter-Area Fractal Dimension	$p = k \bullet a^{\frac{PAFD}{2}}$	Complexity of area shapes, ranging between 1 and 2 with higher values indicating more complex shapes.
MSI (Saura and Martínez-Millán 2001)	Mean Shape Index	$MSI = \frac{\sum_{i=1}^{m} \frac{p_i}{\sqrt{a_i}}}{4m}$	Irregularity of the shapes, with the minimum value for perfect square shapes.
SD (Farina 1998)	Shannon Diversity	$SD = -\sum_{i=1}^{n} P_i \ln P_i$	Variety and relative abundance of the cover type, with the higher values indicating more diversified landuse.
DI (Farina 1998)	Dominance Index	$DI = \ln n - SD$	Dominance of one landuse class over the others, 0 < DI ≤ 1.

* where: m = total number of patches of the class of interest; A = total area of the study area; p = perimeter of class of interest; k = constant; a = area of each class of interest; n = total number of classes; and P is the ratio of a class area to the total area, which reflects relative importance of landuse types.

3. RESULTS AND DISCUSSION

3.1 Area statistics

From the area statistics (table 5) some major changes of landuse can be observed in the past 30 years. For cropland, its area increased from 4% on the 1994 TM image to 13% on the 2000 ETM image. For grass and woodland, its area decreased 5-7% from 72-75% on early MSS to 60-66% on later SPOT, TM and ETM images. For salty grassland, it decreased from 5-7% on the MSS and SPOT to 3% on the TM and ETM images. For water body, it accounts for 8-10% on the MSS, 18-23% on the SPOT and TM, and 9% on the ETM data.

In the study area the large-scale reclamation started in 1992 and increased very rapidly in the past decade. This is confirmed by the increase of cropland shown on the TM and ETM images. In early 1980s, a large reservoir formed in sand dune area because of the construction of a dam in the north. This is shown by the sharp increase of water body area converted from grass and woodland. Salty grassland is one of major kind of landuse class that was reclaimed. Since 1992, salty grassland has decreased very significantly, in association with the rapid increase of cropland, as shown on the 1994 and 2000 images. These major landuse changes are consistent with natural or human events.

Table 5. Area statistics of the land cover types over the 30-year study period.

		1973	1976	1986	1994	2000
Cropland	(ha)	-	-	-	254.3	797.0
	(%)	-	-	-	4.0	12.6
Grass / woodland	(ha)	4746.8	4577.2	4129.9	3811.9	4153.2
	(%)	74.9	72.2	65.2	60.2	65.6
Salty grass	(ha)	331.1	416.4	376.1	202.6	170.7
	(%)	5.2	6.6	5.9	3.2	2.7
Water body	(ha)	476.9	608.8	1143.3	1441.2	547.8
	(%)	7.5	9.6	18.0	22.7	8.6
Bare ground	(ha)	781.3	733.7	686.7	626.1	667.1
	(%)	12.3	11.6	10.8	9.9	10.5

In contrast, some landuse changes reflected by area statistics are not related to natural or human events. For example, the bare ground under natural condition would be stable so that there should not be obvious change of bare ground area. However, according to the area statistics, bare ground increased from 9.9% in 1994 to 12.3% in 2000. While comparing with the area in 1973, the area of the bare ground in 2000 showed 15% decrease. This clearly shows the uncertainty to relate the landuse change to natural and human activities and it is probably largely influenced by the classification accuracy and spatial resolution of the data. We therefore recommend that if the area of detected landuse change accounts for less than 5% of the total area, the uncertainty of change detection can be very significant.

Generally, classified results with a low spatial resolution should show approximately equal opportunity for omission and commission errors related to small patches. The uncertainty in area statistics, therefore, is likely linked to the classification errors caused by the low spatial resolution. In the study area, the poorer classification results were found in association with lower spatial resolution (Zhou *et al* 2004), demonstrated by the higher fluctuation of area statistics results. Concentration on the detected change area, e.g. the temporal trajectory analysis, therefore, seems to be a better and more promising approach.

3.2 Temporal trajectories

From the temporal trajectory statistics, the unchanged area occupied 37.7% of the total area, stable change accounted for 19.6%, and unstable change showed 42.6% (table 6). For the unchanged area, grass and woodland occupied 80.9%. In the stable-change area, cropland converted from other classes accounted for 54.5%. For the unstable-change area, water body interchanged with other landuse classes (not including bare ground) occupied 59.7%.

On the accuracy of the change trajectories, the average accuracies were 90.9%, 78.1% and 40.2%, for the unchanged, stable change and unstable change trajectories, respectively. The overall accuracy of all trajectories was 67.7% (table 6). The unchanged trajectories showed the highest accuracy (all over 90%), while the accuracy of unstable change trajectories was the lowest (all below 60%). Clearly if the classification of all five-stage images confirms the same class at a given location, the likelihood of misclassification is limited. On the contrary, the unstable change trajectories were characterised by frequent change of landuse classes, mostly occurred at the boundaries between classes, the larger classification errors were unavoidable. The much greater number of trajectory cases (combinations) of the unstable change category may also contribute significantly to the higher error level.

Table 6. Area, accuracy and combination statistics of landuse trajectory types

Types	Area		Accuracy					Combi-nations
	Area (ha)	(%)	True cases	(%)	False cases	(%)	All cases	
Grass/wood land	1931.9	30.5	218	89.3	26	10.7	244	1
Salty grass	7.7	0.1	2	100.0	0	0.00	2	1
Water body	47.0	0.7	11	100.0	0	0.00	11	1
Bare ground	400.8	6.3	50	96.2	2	3.9	52	1
Unchanged	2387.5	37.7	281	90.9	28	9.1	309	4
Old cultivation	124.0	2.0	20	80.0	5	20.0	25	6
New cultivation	675.4	10.7	72	83.7	14	16.3	86	16
Abandoned cultivation	128.6	2.0	0	0.00	10	100.0	10	2
Reservoirs / ponds	311.8	4.9	33	84.6	6	15.4	39	3
Stable	1239.9	19.6	125	78.1	35	21.9	160	27
Grass/woodland	435.3	6.9	19	34.6	36	65.5	55	16
Flooded	1618.0	25.5	110	56.1	86	43.9	196	28
Bare ground	655.4	10.3	0	0.0	70	100.0	70	36
Unstable	2708.7	42.8	129	40.2	192	59.8	321	80
Total	6336.1	100.0	535	67.7	255	32.3	790	111

In the past 30 years, less than 40% of the total area was unchanged, while the stable and unstable change accounted for more than 60%. It appears that landuse in the study area has changed dramatically. However, one should note that the stable change only occupied less than 20% of the total area, which indicates the irreversible landuse change. In reality, unchanged trajectories show the original condition of land cover; stable change trajectories show most human-induced changes; while unstable change trajectories are relatively less significant since they tend to show natural (i.e. reversible) land cover change and also contain most of classification errors. Therefore, for landuse change detection study, we recommend that the focus should be on the analysis of unchanged and stable change trajectories, especially the stable change trajectories, because of their higher accuracy and meaningful indication of the irreversible change.

3.3 Spatial pattern

Table 7 summaries the findings related to spatial pattern indices. It shows that SI varies between 0.8 and 0.1 and DI varies between 0.4 and 0.7. The detailed fluctuation over time generally reflects change of spatial pattern. For example, after the construction of a dam in early 1980s, the appearance of the reservoir and reduction of grass and woodlands led to greater landuse diversity, resulted in increasing SD and decreasing DI from 1973 to 1986. From 1994 to 2000, the landuse diversity increased with the large scale cultivation, resulted in higher SD and lower DI from 1994 to 2000. Note that the SD and DI showed reverse trend during the period of 1986 to 1994, while decreasing SD and increasing DI were observed. This could be largely affected by the increasing number of landuse types (from four to five due to the addition of cropland). It is, therefore, reasonable to conclude that the temporal change of SD and DI indicates the trend of landuse diversity and they are not sensitive to the spatial resolution of remotely sensed images, but could be affected by the changing number of landuse classes.

Table 7. Metrics of all landuse classes for five-stage data

Metrics		Classes	1973	1976	1986	1994	2000
Patches metrics	PPU	Cropland	-	-	-	1.515	1.799
		Grass / woodland	0.189	0.584	2.525	0.884	1.278
		Salty grass	0.331	1.042	2.273	0.379	0.884
		Water body	1.136	2.967	7.623	1.484	0.694
		Bare ground	0.521	1.200	1.673	0.616	0.915
	PAFD	Cropland	-	-	-	1.230	1.256
		Grass / woodland	1.307	1.345	1.304	1.328	1.358
		Salty grass	1.216	1.224	1.301	1.237	1.241
		Water body	1.292	1.309	1.291	1.308	1.3967
		Bare ground	1.120	1.249	1.255	1.300	1.284
	MSI	Cropland	-	-	-	1.874	2.614
		Grass / woodland	6.325	7.741	13.690	13.828	11.096
		Salty grass	1.551	1.667	2.729	2.304	1.812
		Water body	2.173	2.038	4.151	3.007	3.204
		Bare ground	2.088	2.784	3.706	3.018	3.274
Pattern metrics	SD	-	0.823	0.889	0.996	0.882	1.084
	DI	-	0.563	0.498	0.390	0.728	0.526

In this study, the PAFD values did not show significant variation between landuse classes. In general, the cropland showed generally less complex shapes than natural land cover types, particularly grass and woodland and water body, but difference in PAFD values are quite small (about 0.10 – 0.15). This result also shows that the PAFD is not sensitive to the spatial resolution of the images.

By definition the MSI is related to spatial resolution. The higher is the spatial resolution, the more details on the object shape are revealed, and thus the higher MSI is observed. This study confirmed the assumption as the MSI showed generally higher values on SPOT, and decreasing values on ETM, TM and MSS, closely related to their spatial resolutions. Comparing landuse types, croplands obviously showed the least irregularity suggesting the fundamental difference between human-induced landuse and natural land cover patterns. An exception, however, was observed on salty grass that showed less MSI than the cropland in 2000. This could be due to that only a small area of salty grass had left after the reclamation in late 1990s.

In this study the result of PPU showed some effects of spatial resolution indicated by general higher value on the SPOT image. However, this pattern was not well supported by the other evidences. The PPU values did not show a recognisable pattern in relation to landuse types, nor on spatial resolution. As a ratio of patch numbers and area, PPU can largely be affected by a number of factors including spatial resolution of the image, classification accuracy and post-classification sorting methods, thus the real spatial pattern that may be revealed by PPU could be well masked.

According to the above analysis, it is suggested that SD, DI and PAFD are not sensitive to the spatial resolutions of multi-sensor images, while MSI is closely related to the spatial resolution. All these four indices have demonstrated good usability as indicators of spatial pattern of landuse/cover types in this study. PPU, on the other hand, did not present itself as a reliable and meaningful indicator for the spatial pattern analysis in this study.

Benson and MacKenzie (1995) and Frohn *et al* (1998) stated that spatial resolution had important effect on most landscape metrics. However, Wickham and Riitters (1995) stated that landscape metrics should not be dramatically affected by the change in pixel size up to 80m. These results appear to be inconsistent. However, taking into account the difference of the metrics discussed in their works, the results of this study confirm the previous work to some extent. For example, the metrics discussed by Benson and MacKenzie (1995) were percent water, number of lakes, average lake area and perimeter, the fractal dimension, and texture, of which some are similar to MSI in principle, thus it is understandable that the influence of spatial resolution was emphasised. On the other hand, Wickham and Riitters (1995) used DI so that it is expected that his finding is confirmed by this study.

4. CONCLUSION

The ability to discriminate the landuse/cover types varies significantly for multitemporal images because of various spatial and spectral resolutions of images acquired by different sensors. The area statistics are capable of showing the general landuse change trends, but the uncertainty caused by area fluctuation due to classification errors may play a significant role to create misleading results. In this study, the poorer classification results were found in association with lower spatial resolution, demonstrated by the higher fluctuation of area statistics results. Concentration on the detected change area, e.g. the temporal trajectory analysis, therefore, seems to be a better and more promising approach.

In the past 30 years, less than 40% of the study area was unchanged, while the stable and unstable change accounted for more than 60%. Unchanged trajectories show the original condition of land cover; stable change trajectories show most human-induced changes; while unstable change trajectories are relatively less significant since they tend to show natural (i.e. reversible) land cover change and also contain most of classification errors. Therefore, for landuse change detection study, we recommend that the focus should be on the analysis of unchanged and stable change trajectories, especially the stable change trajectories.

For spatial pattern analysis, this study suggests that SD, DI and PAFD are not sensitive to the spatial resolutions of multi-sensor images, while MSI is closely related to the spatial resolution. All these four indices have demonstrated good usability as indicators of spatial pattern of landuse/cover types in this study. PPU, on the other hand, did not present itself as a reliable and meaningful indicator for the spatial pattern analysis in this study.

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