

Analysis of Land Cover change Due to Gold Mining in Bombana using Sentinel 1A Radar Data

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Abstract

The discovery of the gold-mine site in Bombana regency since 2008 brings an economic benefit to local society as well as the threat of environmental damage. Environmental damage poses a serious threat considering that mining activities are essentially destructive by altering the landscape and total environmental ecosystem both on land and in coastal waters. To reduce the potential damage to the environment, a regular monitoring of mining areas needs to be performed. In this research, the change of the land cover area in Bombana due to gold mining activity was evaluated using Synthetic Aperture Radar (SAR) data, especially Sentinel-1A data. We processed 10 Sentinel 1A data recorded within 2015 to 2017 that produced high kappa accuracy of 63.6%. During the 3 years monitoring, the open land area gradually increased followed by the increase of the mine-site area and decrease of the vegetation area. The result of the processed data indicated that there was a land cover change in the Bombana area due to gold mining activities. Unfortunately, the absence of sentinel data prior to gold mining activities in Bombana causing land cover changes before and after mining cannot be monitored accurately.

1. Introduction

Since the discovery of a gold mine site in Bombana regency, South-East Celebes, Indonesia in 2008, this area has changed to an hotspot area, not only for people living in this province but also others who live outside. Gold mining activities at this location bring economic benefits to society at a time as well as the threat of environmental damage (Hafid, 2013). Artisanal mining activity (the number is dominant in Bombana) are being accused as a source of environmental degradation. Starting from the destruction of the landscape, the disappearance of surface vegetation, increased erosion, flood events and drought, as well as other environmental damage. Even artisanal miners are regarded as one of the top ten causes of the world's worst pollution (Ahyani, 2011). Environmental damage poses a serious threat considering that mining activities are essentially destructive because they alter the landscape, physical and chemical properties of the soil, and even total environmental ecosystem both on land and in coastal waters. Negative impacts on the coastal areas are caused by river flowing into the sea often used by miners as a medium separating the solid and mine material itself.

In previous research conducting by Nurgiantoro (2016), gold mining activities in Bombana caused significant changes in the quality of bombana waters

as indicated by three indicators: Total Suspended Sediment (TSS) and Chlorophyll-a (Chl-a) concentration. The TSS increased from the year prior to mining activity, averaging 57.94% in 2013 (453.51 g/m³), 53.26% in 2014 (416.54 g/m³), and 63,46% by 2015 (498.19 g/m³). Meanwhile, Chl-a concentration during the observation year indicated the coastal waters of Bombana was in bloom condition and getting a decline in the following year. The mean concentrations of Chl-a were 977.35 mg/m³, 1017.16 mg/m³, and 960.00 mg/m³ in 2013, 2014, and 2015 while in 2001 it was 3718.16 mg/m³.

Considering significant changes on ecology (i.e. spatial and temporal heterogeneities), remote sensing techniques can be an effective approach for the routine monitoring as well as in-situ measurement on the field (Liu et al., 2003, Jaelani et al., 2013 and Mukhoriyah and Trisakti, 2014). To reduce the potential of more severe damage to the environment, a regular monitoring of mining areas needs to be performed. Generally, cloud-free optical satellite imageries were utilized in land used and land cover (LULC) study (Alqurashi and Kumar, 2014, Thunig et al., 2010, Saadat et al., 2011, Coskun et al., 2008). Considering the lack of cloud free over the area of study, an active satellite data

that have ability to penetrate clouds was used for LULC mapping (Chatziantoniou et al., 2017, Waske, 2014, Werner et al., 2014, Abdikan et al., 2016 and Gruber et al., 2013).

Therefore, the main purpose of this research is to evaluate the change of land cover area in Bombana due to gold mining activity using Synthetic Aperture Radar (SAR) data, especially Sentinel-1A data. Monitoring of earth-surface often disturbed by cloud cover. It can be overcome by SAR data that can penetrate clouds, making it effective to observe land cover changes clearly (Balzter et al., 2015). Sentinel-1A, which was launched in April 2014 provides a C-band image of either one or two polarizations with acquisition period of 12 days. Data were obtained via three methods: Stripmap (SM), Interferometric Wide Swath (IW), Extra Wide Swath (EW) and Wave (WV) with different processing levels (Abdikan et al., 2016).

2. Methods

2.1 Study Area

Bombana is one of regency in Southeast Sulawesi Province. Geographically, it is located near the equator, extending from north to south between 04°22'59.4" to 05°28'26.7"S and from west to east between 121°27'46.7" to 122°14'09.4"E. Administratively, Bombana consists of 22 districts and 140 villages. This regency is bordered by

Regency of Kolaka and South Konawe in the north, the Flores Sea in the south, Regency of Muna and Buton regency in the east, and Regency of Bone in the west. Bombana has a land area of ± 3316.16 km², where the marine area is estimated to cover an area of ± 11,837.31 km² (Figure 1).

2.2 Data

The data used in this research was SAR Sentinel 1A Level-1 with Ground Range Detected High-resolution (GRDH) format that was recorded from 2015 to 2017. The data are in the path of 61, Frame of 606, Beam mode of Interferometric Wide Swath (IW) and frequency: of C-band (Table 1).

2.3 Pre-Processing

Pre-processing Sentinel-1 (Level 1, GRDH) data was performed using the Sentinel-1 Toolbox (S1Tbx) attached to STEP software. The initial process involved applying orbit correction to update the orbital file in the metadata, to provide accurate position and satellite speed. Then, radiometric calibration was performed to produce sigma nought value (σ^0). In order to reduce the speckle effect of the SAR image, a speckle filtering with 5×5 gamma map was performed. If Sentinel-1A image was in reverse position, then geometric distortion need to be corrected by applying a geometric correction with Doppler Range Terrain Correction.

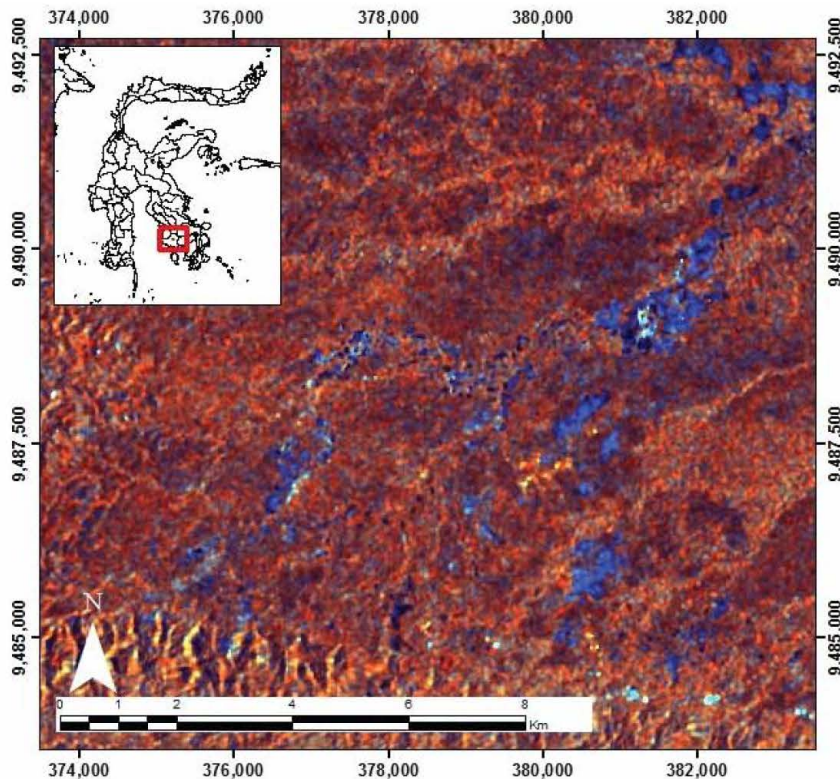


Figure 1 : Area of Study (presented based on Sentinel 1A data)

Table 1: List of Sentinel 1A data

No	ID Scene	Date	Orbit
2015			
1.	S1A_IW_GRDH_1SDV_20150302T213503_20150302T213528_004858_0060D3_7A9D	2015-03-02	4858
2.	S1A_IW_GRDH_1SDV_20150326T213503_20150326T213528_005208_006937_66B1	2015-03-26	5208
2016			
3.	S1A_IW_GRDH_1SDV_20160811T213514_20160811T213539_012558_013AC4_62B9	2016-08-11	12558
2017			
4.	S1A_IW_GRDH_1SDV_20170315T213517_20170315T213542_015708_019DA7_7F83	2017-03-15	15708
5.	S1A_IW_GRDH_1SDV_20170327T213517_20170327T213542_015883_01A2E2_A68A	2017-03-27	15883
6.	S1A_IW_GRDH_1SDV_20170408T213517_20170408T213542_016058_01A81E_16E8	2017-04-08	13608
7.	S1A_IW_GRDH_1SDV_20170420T213518_20170420T213543_016233_01AD7A_E67B	2017-04-20	16233
8.	S1A_IW_GRDH_1SDV_20170502T213518_20170502T213543_016408_01B2C6_459D	2017-05-02	16408
9.	S1A_IW_GRDH_1SDV_20170514T213519_20170514T213544_016583_01B818_1AF4	2017-05-14	16583
10.	S1A_IW_GRDH_1SDV_20170526T213520_20170526T213545_016758_01BD79_88BF	2017-05-26	16758

The Digital Number (DN) value of the SAR data was then converted to the backscatter value in decibels (db). Some of these corrections were useful for reducing topographic effects but resulting in different slope correction effects. Here, the slope correction model from Kelldorfer et al., (1998) was used to correct the slope effects.

$$\sigma_c^\circ = \sigma^\circ \frac{\sin \varphi}{\sin \theta}$$

Equation 1

σ_c° is backscatter coefficient of SAR after calibration, σ° is original backscatter coefficient of SAR, φ is Local Incidence Angle, and θ is SAR Incidence Angle at the center of image (Zhou et al., 2011). After slope normalization, a vector data was used to subset the area of study. All of data was then exported into KMZ format that was overlaid in Google Earth.

2.4 Image Classification

For image classification, Maximum Likelihood on ArcGIS software was used. This plugin provides some tools for classification processing and faster calculation. SAR data was analyzed based on the RGB color system, where VV, VH and VV/VH were assigned as Red, Green and Blue, respectively.

2.5 Accuracy Assessment

Accuracy assessment was performed for validating a classified image and 'true-field' object following kappa coefficient formula (Sampurno and Thoriq, 2016):

$$Kappa (k) = \frac{N \sum_i^r x_{ii} - \sum_i^r x_{i+} x_{+i}}{N^2 - \sum_i^r x_{i+} x_{+i}} \times 100\%$$

Equation 2

K is Kappa Coefficient, $\sum_{i=1}^I \pi_{ii}$ is the total proportion of the main diagonal of observation frequency and $\sum_{i=1}^I \pi_{i+} \pi_{+i}$ is total major marginal proportion of observation frequency. Kappa analysis tool follows the rule of Kappa <0.20 as low correlation; 0.21-0.40 is Fair; 0.41-0.60 is enough, 0.61-0.80 is strong and 0.81 – 1.00 is very strong (Murti, 2011)

2.6 Area Calculation

After performing the accuracy assessment, the area of each object class was calculated to analyze the land cover change within the time range of 2015 to 2017.

3. Result and Discussion

The result of land cover classification of Sentinel 1A SAR data within the range of 2015 to 2017 resulted in 4 classes: mining area, open land, vegetation and built area with a total area of 109,151,427 m². Land cover from 2015 to 2017 is dominated by open land compared to vegetation area class (Figure 2).

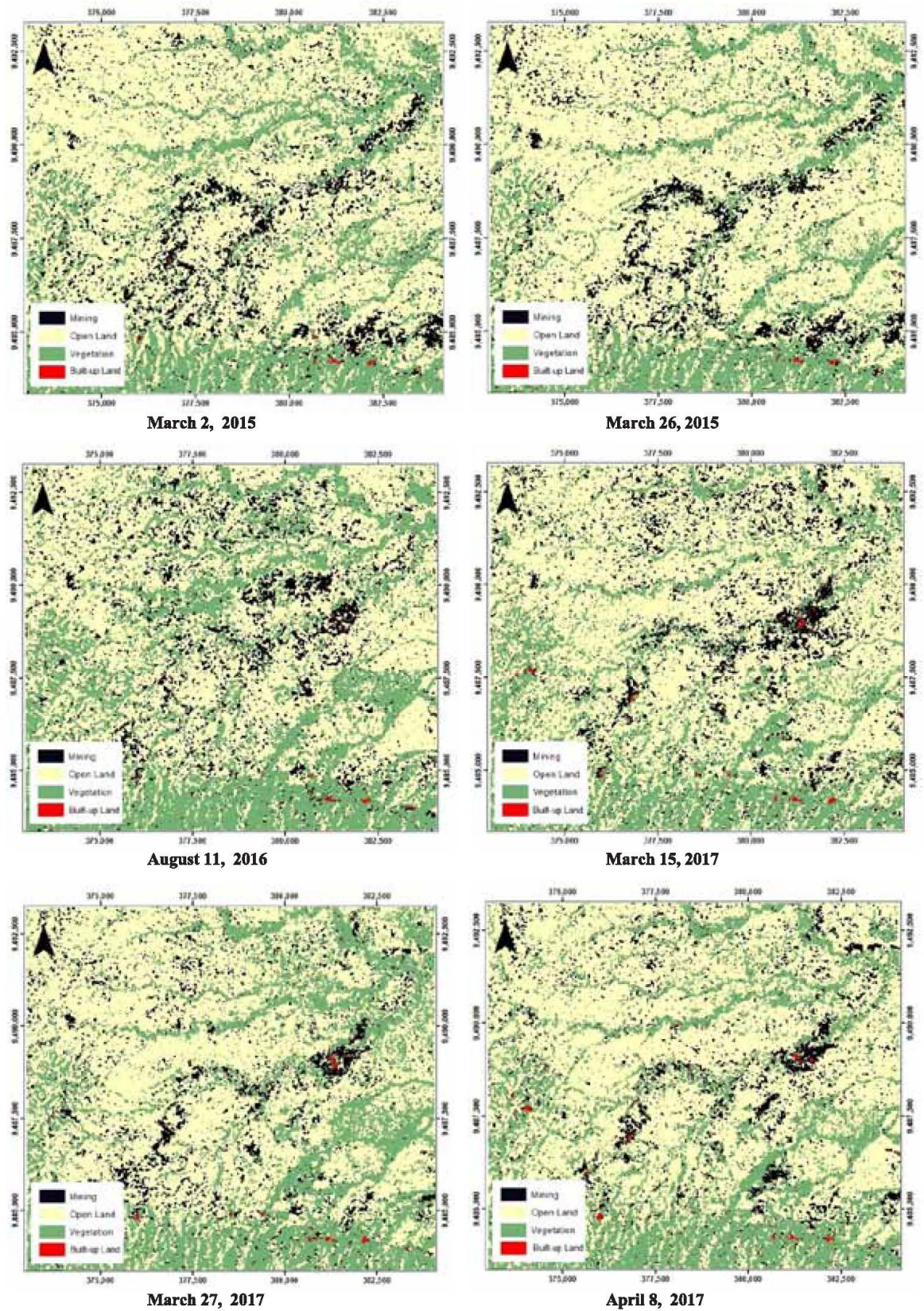


Figure 2: Land cover at specific time (Continue next page)

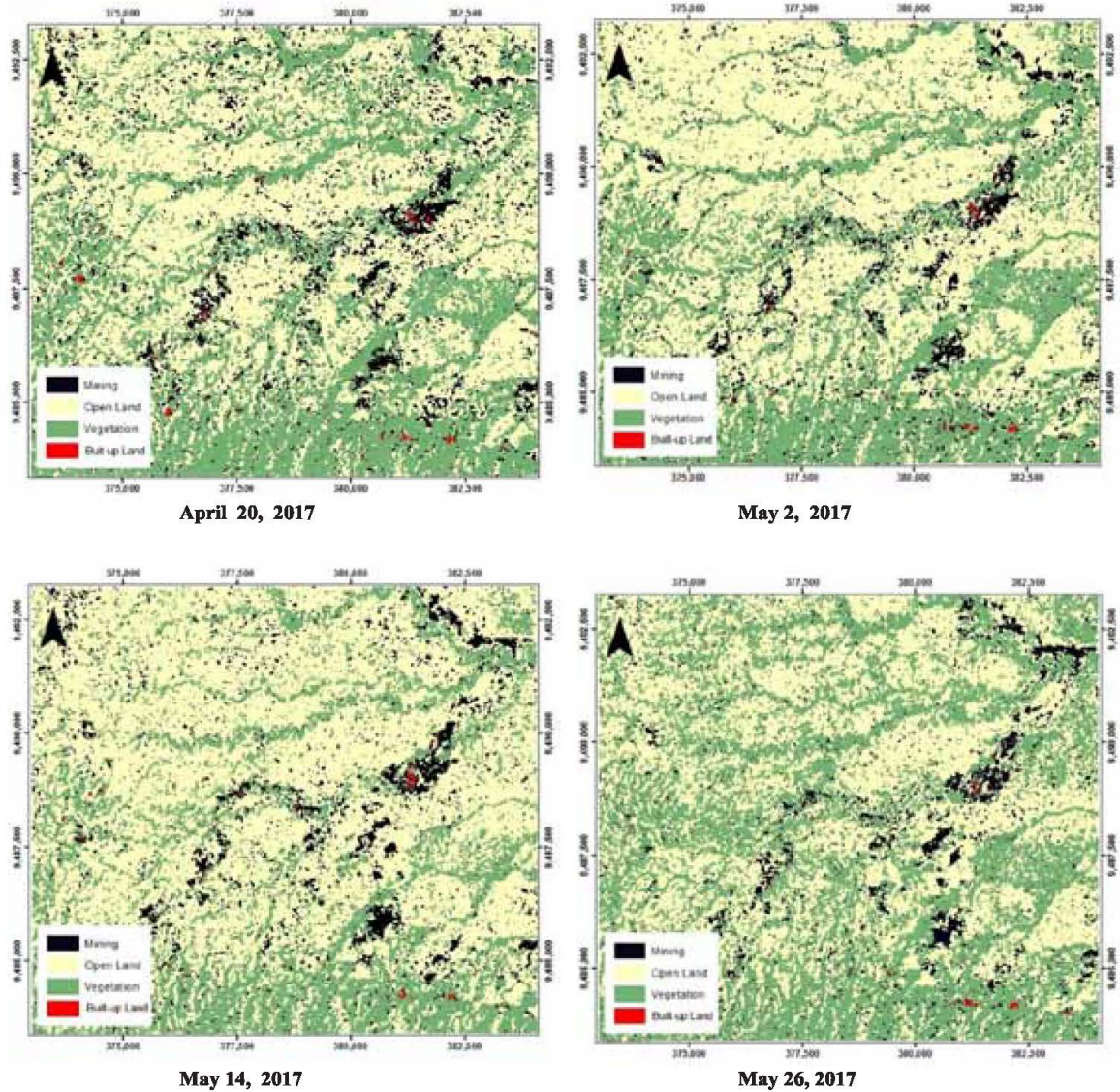


Figure 2: Land cover at specific time

It was indicated that open-mining activity causes the impact on spatial land conversion from forest to open land (Hidayat et al., 2015). The highest increase of open land occurred on May 14, 2017. It came as conversation from the class of mine and vegetation area into open-land. Vegetation area (e.g forest) has been opened to be used as mining area, other than that the area of the mine that had been closed and turned into open land. The mining area experienced the lowest decline on May 26, 2017 (Table 2).

The environmental damage caused by the gold mine since 2008 has prompted environmental activists such as Wahana Lingkungan Hidup to state

explicitly that Bombana's mining site has been severely damaged by gold mining in 2008. This prompted the Bombana Government to temporarily suspend all mining activities to prevent widespread environmental degradation. The area of the vegetation class has the highest increase and at the same time the lowest decrease of the mine area on May 26, 2017. This is influenced by the increasing awareness of the environment. Meanwhile, the area of built-up land within the period 2015 - 2017 fluctuated up and down. The gold miners made traditional and non-permanent house or tent when needed and were disassembled after they were finished, some of which left behind (Table 3).

Table 2: Area of each class

No	Acquisition date	Area (m ²)				
		Mining	Open land	Vegetation	Built-up	Total
1	20150302	10957974	67858542	30171261	163648	109151427
2	20150326	10107030	71022522	27904779	117097	109151427
3	20160811	11749722	59851389	37407211	143105	109151427
4	20170315	11755755	67415310	29611775	368585	109151427
5	20170327	9340073	65678517	33915232	217605	109151427
6	20170408	9105392	67843305	31824349	378380	109151427
7	20170420	9387880	57303081	42149763	310702	109151427
8	20170502	7529299	61666683	39755686	199759	109151427
9	20170514	7837215	70848474	30221393	244345	109151427
10	20170526	6759313	53423360	48776160	192595	109151427

Table 3: Confusion matrix

Classified data	Class	Reference data				Row	User Accuracy (%)
		Mining	Open land	Vegetation	Built-up		
	Mining	90	60	0	0	150	60
	Open land	8	183	9	0	200	91.5
	Vegetation	13	20	117	0	150	78
	Built-up	0	40	6	54	100	54
	Column	111	303	132	54	600	
OVERALL = 74%							
KAPPA = 63.6%							

Information from Google Earth imagery is further used as a reference to test the results of land cover classification. Where the classification data in ArcGIS changed its format into KML form to be opened in Google Earth. This study uses Google Earth imagery with the imaging date on December 31, 2016. Sentinel 1A radar data processing results produced Kappa accuracy of 63.6% (high accuracy). The classification results show that 60%, 91.5%, 78% and 54% were in accordance with its class of mine area, open land, vegetation and built-up area, respectively.

4. Conclusions

We had processed 10 Sentinel 1A data recorded within 2015 to 2017. The data were dual polarization and in GRD format. Based on 3 years data, an open land area gradually increased followed by the increase of the mine-site area and decrease of the vegetation area. The result of processed data indicated there was a land cover change in Bombana area due to gold mining activities. Unfortunately, the absence of sentinel data prior to gold mining activities in Bombana made land cover changes before and after mining not to be monitored accurately.

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