CHARACTERISATION OF LONG-TERM VEGETATION DYNAMICS FOR A SEMI-ARID WETLAND USING NDVI TIME SERIES FROM NOAA-AVHRR

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ABSTRACT:

The Niger Inland Delta represents a flat area of around 40.000 km², which is annually inundated by the Niger River system. As the flood is driven by the rainfall in the catchment areas, it is not linked to the low precipitation of the Sahelian region. Thus, local rainy season and inundation show a temporal delay of 3 months and the Niger Inland Delta's ecology can be described as a mosaic of permanent, periodical and non-periodically flooded areas. AVHRR GIMMS Data provide NDVI values over 25 years with 2 data / month on a 8 x 8 km grid. Dynamics in vegetation density were modelled from the temporal variability of the NDVI. Therefore each time series was detrended and transformed into the frequency domain. The power spectra then were decomposed into a long-term cyclic component by applying a FIR with a cut-off frequency slightly lower 1 cycle / year, a seasonal (annual) and an irregular component. For modelling the seasonal component of a time series, an algorithm is proposed that reduces the no. of frequencies by referring to the most significant ones, but at the same time keeps different time series comparable, as all frequencies are retained that were needed to preserve an a-priori defined level of information for any of the time series.

1. INTRODUCTION

To investigate the state and/or the amount of vegetation is one of the main objective in the field of land surface related remote sensing applications. A prerequisite for successful monitoring of vegetation cover is the availability of frequent data that are internally consistent over a sufficient period and that provide information on the spatial complexity as well as on the temporal dynamics of vegetation. Many methods and in particular various vegetation indexes have been introduced, to quantify certain vegetation parameters. All of them take into account that vivid green vegetation shows a specific reflection signal in the red and near infrared part of the electromagnetic spectrum. The normalised difference vegetation index (NDVI) has become a commonly used index that is routinely derived from NOAA AVHRR images since mid 1981. To reduce atmospheric effects and noise, present in the direct reflectance measurements of an individual image, considerable effort has gone into the generation of multi-day composites. Such vegetation index composites proved to be very sensitive to a wide range of biophysical parameters, among them photosynthetically active biomass (Goetz et. al., 1999) or the presence of green vegetation (Myeni et al., 1995).

Numerous studies have been conducted that use AVHRR NDVI data to analyse vegetation parameters on a regional to global scale, among them the estimation of terrestrial net primary production (npp) (Ruimy et. al., 1994) or the analysis of changes in vegetation phenology (Heumann et. al., 2007). The long term NDVI time series from AVHRR were related to climate variables such as air temperature or rainfall data with the objective of revealing geo-biophysical linkages for observed changes in vegetation parameters (greenness or npp) (Herrmann et. al., 2005, Xiao & Moody, 2005).

The regional focus of this paper is the Niger Inland Delta, situated in the western Sahel region in Africa (see. Figure 1. for details). Whereas precipitation is the main constraint for vegetation growth in the semi arid Sahel, the Inland Delta's biosphere relies on water that flows in the region during the annual flooding period. This paper aims to analyse the long-term dynamics of vegetation cover in the Niger Floodplain over a 25 year period, based on 15day-composites of NDVI values from NOAA-AVHRR. To detect influences on vegetation cover for different time scales each time series was decomposed into 3 components according to the conventional component model. For this unbundling each time series was transferred into the frequency domain by a Discrete Fourier Transformation (DFT), making use of the advantages of the globally addressed (in terms of "the entire time series") operators of the frequency domain.

2. GEOGRAPHIC PARAMETERS FOR THE NIGER INLAND DELTA

The geographic term „Niger Inland Delta" stands for a vast, extremely flat area of some 10.000 km² extend, which is annually inundated by the water of the Niger - Bani river system during September to December. The ecology of the delta can be described as a mosaic of permanently, periodically and episodically flooded pat-tern, which contrasts sharply to the semi-arid environment of the Sahel. Spatial and temporal extent of the flood patterns vary due to fluctuating water supply by the river system caused by irregular rainfall in the catchment areas. Thanks to a comparatively good availability of (surface) water, the Niger Inland Ecosystem serves as stop-over for many migrating birds and other wildlife species as well as economic base for farmer and pastoral people. To foster the sustainable usage of its natural resources and to protect this natural heritage, the entire Niger Inland Delta became RAMSAR site in 2004 (RAMSAR 2008). (see Fig. 1 for an overview of the area)

In contrast to its semi-arid environment, the Niger Inland Delta's ecology can be described by a mosaic of permanently, periodically and episodically flooded areas. Their extent varies both in scale and in time due to irregularities of amount and seasonal distribution of annual rainfall in the catchment areas and the resulting water supply contributed by the Niger-Bani system. As it takes some time for the water to run off from the catchment areas in the Fouta Julon Mountains (Guinea) towards the Niger Inland Delta, the inundation occurs with a temporal delay of some months, compared with the rainy season. Flooding starts in mid October at the southern entry of the Delta and lasts until end of December / mid January.

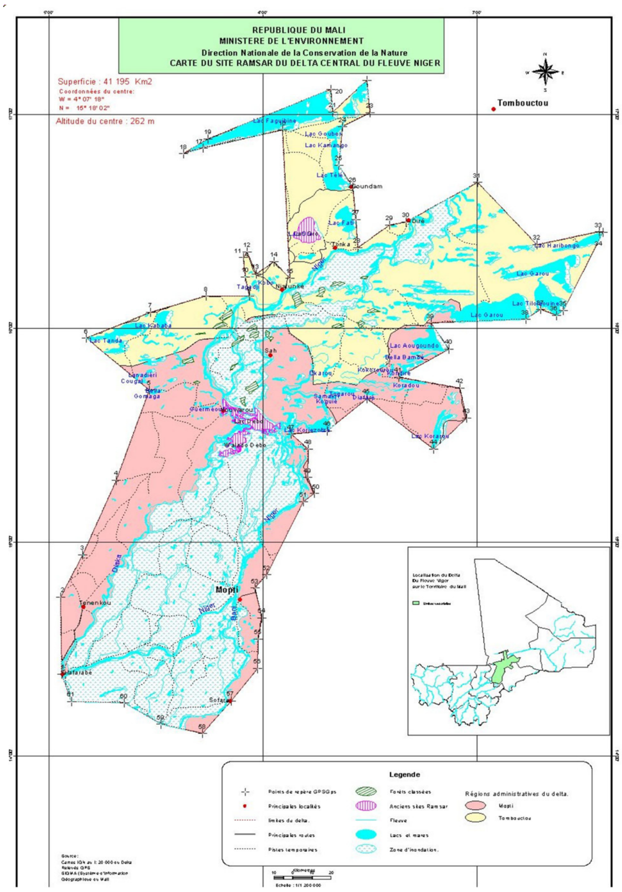

Figure 1. Niger Inland Delta (RAMSAR site) scale 1:200.000 http://www.wetlands.org/Reports/Country_maps/Mali/1ML001/1ML001map.jpg

From this relation result 2 seasonal variations, a rainy ↔ dry phase and a flooding ↔ drainage phase, as illustrated in Fig. 2. They appear with a temporal delay of about 3 to 4 months and are superimposed by a 3^{rd} undulation that counts for several years (period between dry years and years with sufficient precipitation). This latter variation is dominantly affected by the 2 seasonal ones, but high spatial variability of precipitation does not permit a causal linkage. In particular, low amount of rainfall in the delta may profit from extended rainfall in the head-waters, thus inducing reasonable extent of flooding.

The availability of water represents the main restricting factor for vegetation growth in the Sahel. Vegetation follows the above described water cycles with a temporal delay, which varies from few days (germination of grasses) up to several months (death of trees caused by lack of water). A development of (annual) grasslands with sparsely distributed patches of shrubby vegetation (dominantly composed of Combretaceae sp.) is characteristic for the Sahelian landscape (Breman and DeRidder 1991). According to (LeHouérou 1989), these vegetation pattern can be categorised into the following 3 layers (see Fig. 2 for a scheme):

(a) grass layer with annual grasses and herbs (height 40 cm – 80 cm)
(b) shrub layer (height 50 cm – 300 cm)
(c) tree layer, sparsely distributed single trees (height 3 m to 6 m)

Ligneous layers of shrubs and trees cover only small parts (up to 25 %) of the surface, while the grass layer extend over up to 80 %, (Kußerow 1995). Annual grasses are withering during dry season, thus grassy layers are affected and/or destructed by bush fires and strong winds. Pat-terns of bare soil appear as a result, that extend during the mid- and late dry season. The generally low vegetation cover therefore disappears periodically completely.

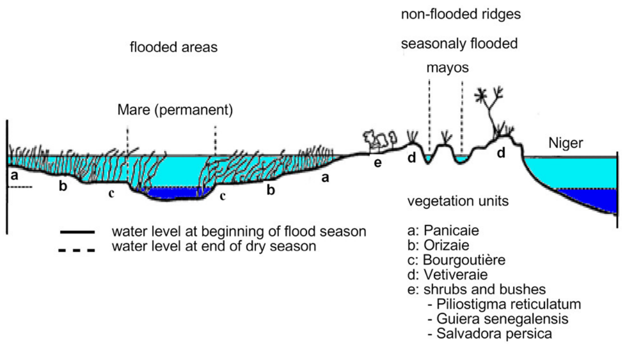

Figure 2. Subsection of the Niger Inland Delta - landscape profile and vegetation pattern, adapted from (Diallo 2000)

3. DATA AND METHODS

3.1 GIMMS 15-day NDVI composite data

The GIMMS (Global Inventory Monitoring and Modelling Study) NDVI data record combine measurements from several satellite sensors. To ensure consistency between the multi-temporal data, several corrections for a wide range of factors that affect the calculation of NDVI values have to be applied. According to (Pinzon et. al.,. 2005) GIMMS data are corrected for sensor degradation and intercalibration differences, global cloud cover contamination, viewing angle effects due to satellite drift, volcanic aerosols, and low signal-to-noise ratios due to sub-pixel cloud contamination and water vapour. A well known fact are the shortcomings of the AVHRR sensor design for a vegetation monitoring, as for instance the AVHRR channel 2 (nIR) overlaps a wavelength interval in which considerable absorption by atmospheric water vapour occurs (Steven et al., 2003, Cihlar et. al., 2001).

This global dataset, known as the GIMMS NDVIg, is the only publicly available AVHRR dataset to extend from 1981 to 2006 (Tucker et. al., 2005). Due to the correction scheme it is a dynamic data set, that must be recalculated every time a new period of data is added. The Niger Inland Delta and a small buffer of surrounding area is covered by 1298 AVHRR pixel on a 8 km spatial resolution and each of these GIMMS time series consist of 612 data points, covering 25 ½ years from July 1981 until December 2006 with a scan frequency of 2 data / month. This work was done with the updated GIMMS data that were release in 2007.

3.2 Decomposition of NDVI time series

Provided that the NDVI value represents the photosynthetic active vegetation amount, the dynamics of vegetation cover can be characterised by the temporal behaviour of the NDVI value. Thus, NDVI values for a specific pixel over the period from July 1981 to December 2006 will be considered as a time series.

For an analysis of the statistical characteristics - mean, variance and auto-correlation function (acf) - a given time series needs to be stationary. The GIMMS NDVI doesn't fulfill this constraint, as they contain significant cyclic (seasonal and/or multi-annual) components. To derive stationary time series, each NDVI series x_t is decomposed into the following components:

(a) long-term mean $\bar{x}_t$
(b) Cyclical Component c_t
(c) Seasonal Component s_t
(d) Irregular Component i_t

Where the cyclical component consists of a (linear) trend m_t and long term (multi-annual) anomalies a_t. The latter model variations that last over more than 1 year, or that are even not periodically. Variations with periodicities shorter than 1 year are modelled within the seasonal component. The last component i_t describes short term anomalies and allows therefore an interpretation of alterations of the variance of the NDVI signal. It is supposed in the context of this work that all components superimpose, so as to the time series can be written as:

$$x_t = m_t + a_t + s_t + i_t \quad (1)$$

This decomposition of a NDVI time series aims the differentiation of long-term and seasonal dynamics as well as an interpretation of alterations from these periodical behaviour.

3.3 Determination of the Cyclical Component c_t

As c_t models long-term components of the NDVI signal, it can be separated by filtering the time series with a low-pass filter. To design an appropriate filter and to apply filtering efficiently, the time series was transformed into the frequency domain with a Discrete Fourier Transformation (DFT). According to (Meier and Keller 1990) describes

$$X_T(f) = \int_{-\infty}^{\infty} X(\hat{f})\, W(f-\hat{f})\, d\hat{f} \quad (2)$$

where $X(\hat{f})$ = Fourier transform
$W(f-\hat{f})$ = weighting function for the observed time series

the filtered estimation of the spectral density $X_T(f)$ for a time series with finite length. The Fourier transform Y(f) of a filtered signal then results from

$$Y(f) = |H(f)|^2 \cdot X(f) \quad (3)$$

where H(f) = filter transfer function

A moving average (MA), with window size 24, could serve as a simple realisation of such a low-pass filter. As MA-filter show significant side lobes in their step response, these kind of filter produce a leakage for the filtered time series. Furthermore, the negative values around the odd side lobes result in a phase shift of 180° for the filtered signal in these parts. Both disadvantages can be avoided by using a Raised Cosine filter as FIR.

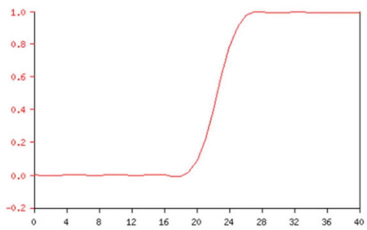

Figure 3. normalised step response of the used FIR filter, due to a sampling rate of 2 / month the value 24 represents a frequency of 1 year^{-1}

3.4 Determination of the Seasonal Component s_t extracting significant frequencies

Seasonal variations in the NDVI signal can be modelled with the phase mean or stack method in the time domain. This algorithm estimates the seasonal component by calculating mean values for each observation date of a year as given in (4)

$$\hat{s}_t = \sum_{r=1}^{24} \left(\left(\frac{1}{25} \sum_{n=1}^{25} \left[x_r(n) - c_r(n) \right] \right) \cdot s_r(t) \right) \quad (4)$$

where r = date of observation within the year (r = 1, …, 24)
n = year of observation (n = 1, …, 25 – [1981 – 2006])
$\left[x_r(n) - c_r(n) \right]$ = time series adjusted for c_t
$s_r(t) = \begin{cases} 1, if\ \ t\ \ belongs\ \ to\ \ r \\ 0, else \end{cases}$

While this approach gives direct access to time related information such as the date of the annual max./min NDVI value or the temporal run of the NDVI curve, an analysis in the frequency domain provides information about the frequencies / periodicities of NDVI dynamics. But due to the great number of data points also the no. of frequencies goes usually beyond the scope of interpretation for longer time series. Reducing the number of frequencies should preserve the information (Σ of power for all frequencies) of a time series as much as possible.

A formal selection of a set of frequencies would only be suitable, if one could a-priori specify the range of relevant periodicities within the time series and adjust the band of preserved frequencies according to this knowledge. Otherwise information about the time series would randomly discarded. If one retains for instance the first few frequencies, one preserves a rather rough approximation of the time series, as these frequencies correspond to the low frequent parts of the signal. Using the largest few frequencies would preserve the individual time series much better, but makes them no longer comparable, as different parts of the signals would be kept.
(Möhrchen, 2006) proposes the use of one subset of frequencies for all time series, thus achieving, that all series have the same dimensionality (In the context of a feature space point of view on the time series, frequencies represent the components of the feature vector that characterises an individual time series.) and keeping them comparable. A frequency belongs to the subset, if it is necessary to preserve an a-priori defined level of information for any of the time series. Where all frequencies of a given time series are sorted according to their magnitude. And the information level is calculated cumulative, starting with the largest frequency, for each time series individually.

3.5 Analysis of the Irregular Component i_t

After subtraction of the long-term mean, the Cyclical and Seasonal Components from the original time series remains the Irregular Component. This part represents a time series that is stationary in wide-sense, as the variance is not independent from time. The annual aggregated variance differs between years, especially for pixel at the edges of the Inland Delta that are not flooded regularly. Provided that the variance is constant over the period of 1 year, the quotient of the Irregular Component and the variance results in a time series that is nearly stationary.

4. DISCUSSION OF RESULTS

The individual components of the time series provide specific information about the character of the underlying vegetation dynamics. The long term mean (calculated for the entire period of 25 ½ years) varies a lot between pixel that cover areas in the central Inland Delta and those that cover the edges of the Floodplain next to the semi arid environment. The NDVI values variability of a specific time series is significantly positive correlated with the long term mean. Thus, areas with overall high NDVI values show higher variability too.

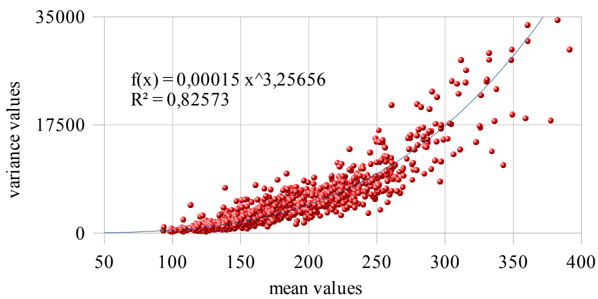

Figure 4.: relation between long-term mean and variance of the NDVI values

The following conclusions for the Cyclical and Seasonal Component will be illustrated, using pixel listed in Table 5 that represent the main ecological categories of the Niger Inland Delta. The more an area is located towards the edges of the delta, the higher its variability in dynamics with low frequencies.

pixel ID	description: located	ecological category
13 31	western edge, close to delta mort	periodically flooded, semi-arid surrounding
15 45	central delta, southern part	flooded
15 48	central delta, southern part	flooded
18 26	northwestern edge	episodically flooded
17 29	Lake district	regularly flooded
20 26	North of Lake Debo	regularly flooded, semi-arid surrounding
16 49	central delta, southern part	flooded
19 43	central delta, southern part	flooded

Table 5. Reference pixel for Cyclical and Seasonal Component

The Cyclical Component unfolds dynamics that last for more than one year. It describes therefore relations between wet and dry years. Clearly visible in Figure 6 is the drop in vegetation cover during the dry years 1984 / 85 and the strong recovery followed 1986 / 87. The 2nd half of the 1980 years and the beginning 90-ies had vegetation cover below the long-term mean, while the mid 90-ies showed a at least for parts of the Inland Delta a recovering of vegetation above the long-term mean.

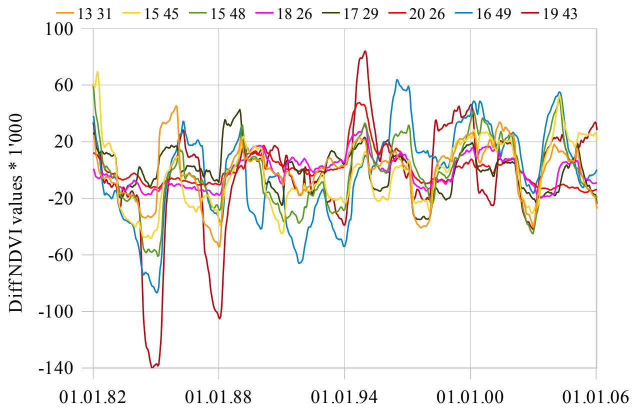

Figure 6.: Cyclical Component (lag 24) represent dynamics with periodicities greater 12 month

A discrimination of pixel according to their month of highest vegetation density can be done with the Seasonal Component (Figure 7). While all pixel show the vegetation drop during the late dry season (May / June), the different causes for vegetation growth result in specific dates of maximum vegetation cover. Areas that are mainly influenced by the semi arid rainfall and not flooded, have their maximum vegetation during end of August or early September. Contrary to this, flooded areas show maximum vegetation during October / November and these extrema show significantly higher values see pixel 19 43 as an example for this ecological category.

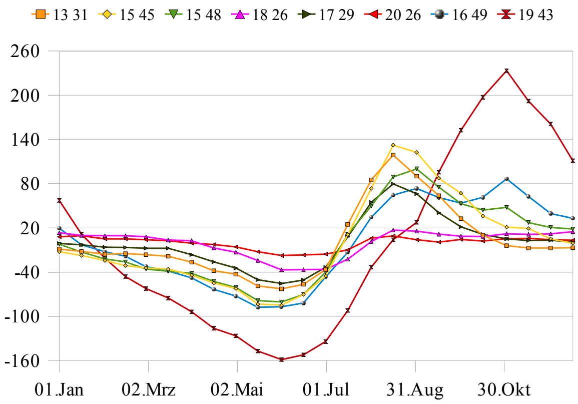

Figure 7.: Seasonal Figure derived with phase mean algorithm

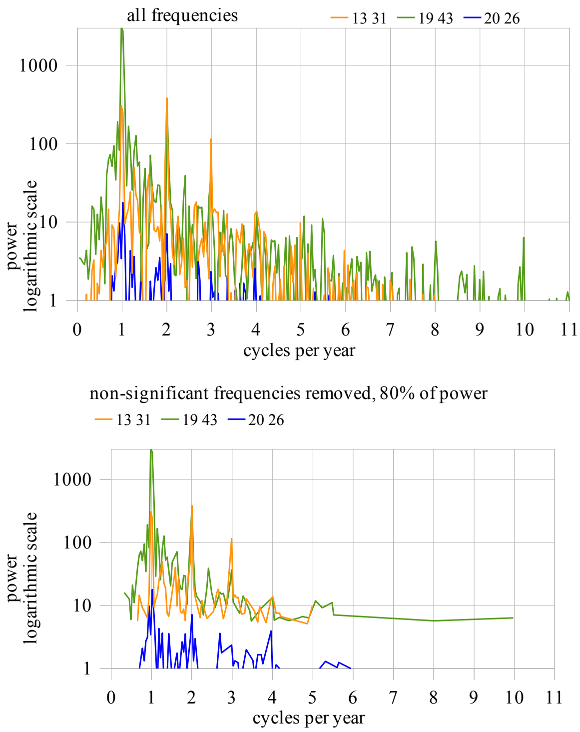

Figure 8.: power spectra for low-pass filtered time series; top – a) all 294 frequencies, bottom – b) only frequencies that preserve min. 80% of total power for each of the time series

The Analysis of seasonal features in the frequency domain can be reduced to the question, which frequencies shall be considered as significant for the seasonal figure. As explained in Section 3.3 of this paper, it is mandatory to retain the same set of frequencies throughout all time series to ensure the comparability between different series. The effect of reducing the no. of frequencies is shown in Figure 8b, where the lower graph shows a reduced spectrum to 80% level of power. This preserved information level is achieved with only 25% of the original 294 frequencies. Even a nearly complete preservation of the information of the time series (99% level of power) yields to a reduction in frequencies to approx. 75% of the original frequencies (223 out of the 294).

After normalisation with the annual variance, the irregular component should form a stationary time series. If so, no specific feature should be detectable within the series. This is true for some time series but as can be seen in Figure 9 it is not for all the case. While the series from pixel 19 43 can treated as stationary for most of the time, the series from pixel 13 31 shows significant extrema. This gives evidence that the seasonal figure is imperfectly modelled with the approaches suggested in this paper (and therefore seasonal features fall partially by mistake into the irregular component) end / or the vegetation dynamics contain significantly non-periodic elements. Therefore a non-stationary time series for an irregular component points out a not periodically growth of vegetation due to an episodically flooded area.

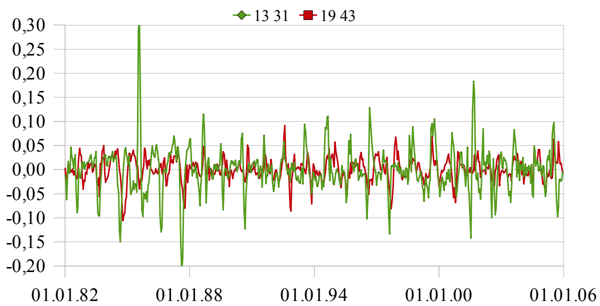

Figure 9.: examples for the Irregular Component, the one for pixel 13 31 shows strong extrema

5. SUMMARY AND CONCLUSIONS

Long-term dynamics are clearly detectable within the NDVI GIMMS time series. These features can be extracted by filtering the time series with an appropriate FIR. Modelling the seasonal dynamics is somewhat more ambiguous. The phase mean algorithm treats all values of a certain acquisition date as source for a mean value that is representative for the period of the entire time series. Every difference between a value of the time series and the corresponding modelled phase mean is treated as part of the Irregular Component. If the seasonal figure is modelled from the power spectra of the Fourier Transform, the shape of the figure depends on the no. of frequencies that is used. The Irregular Component of the time series contains information about non-periodic dynamics of the vegetation cover. These are significantly present in the time series as the extent of flooding varies widely between the years.

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