Introducing a New Concept for Grassland Monitoring: The Multi-temporal Grassland Index (MtGI)

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*Abstract: The monitoring of forage mass in managed grasslands is of key importance because it equals yield. The spatially explicit determination of removed forage mass in multi-cut grasslands is a non-solved problem and the knowledge would enable improved fertilizer management. Therefore, the objective of this contribution is the development of a remote sensing-based method to derive forage mass after grassland is cut. For this purpose, we propose a new concept for vegetation monitoring which is based on the multi-temporal acquisition of super high resolution UAV-based RGB-imagery. From the acquired data it is possible to derive the RGB-Vegetation Index (RGBVI) (Bendig et al. 2015) and sward height (Bareth et al. 2015). The latter is based on the concept of Crop Surface Models (CSMs) which is based on multiple UAV campaigns during phenology (Hoffmeister et al. 2010). The study was carried out at the long-term Rengen Grassland Experiment (RGE) in Germany in 2014. The RGE is conducted by the INRES (*Institute of Crop Science and Resource Conservation*) of the University of Bonn, Germany (Schellberg et al. 1999). From the combination of the UAV-derived data sets, sward height and RGBVI, the computation of the Grassland Index (*Grass*I) is possible (Bareth et al. 2015). In contrast, the newly proposed concept for grassland monitoring is based on two UAV-campaigns per growth: direct before (t_1) and direct after (t_2) cut. From the two time windows, the Multi-temporal Grassland Index (MtGI) is calculated. The MtGI is a NDVI-like vegetation index but includes temporal change in its equation. Applied on remote sensing data, it can be considered as a spatio-temporal vegetation index. The MtGI is highly correlated (R^2 = 0.74) to destructively measured forage mass and therefore, bears a promising potential for non-destructive and automated forage mass mapping in managed grasslands with low-cost UAVs.*

1 Introduction

Monitoring forage mass on managed/multi-cut grasslands, such as extensive or intensive pastures or hay and silage meadows, is an important step towards optimising yield and nutrient balancing/budgeting. Deriving spatially high resolution information about removed forage mass with each cut is a non-solved problem and the knowledge would enable improved fertilizer management.

Site specific fertilizer application as part of Precision Agriculture (PA) can aid in the decision making process (SCHELLBERG et al. 2008). However, manual measurements of forage mass, such as clipping or disc meters/rising plate meters and spectroradiometer measurements cannot meet the requirements to produce a high resolution assessment of the within-field heterogeneity of standing biomass and nutrient status (BARETH et al. 2015; HOLLBERG & SCHELLBERG 2017).

Therefore, the objective of this contribution is to further investigate the potential of RGB imaging with low-cost UAVs for managed grasslands as introduced by BARETH et al. (2015). For

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this purpose, we propose a new concept for vegetation monitoring in general which is based on the multi-temporal acquisition of super high resolution UAV-based RGB-imagery. From the acquired data it is possible to derive the RGB-Vegetation Index (RGBVI) (BENDIG et al. 2015) and sward height (BARETH et al. 2015). Sward height can be spatially derived by applying the concept of Crop Surface Models (CSMs) which is based on multiple UAV campaigns during distinct phenological stages (HOFFMEISTER et al. 2010) on grasslands. From the combination of the UAV-derived data sets, sward height and RGBVI, the computation of the Grassland Index (GrassI) is possible (BARETH et al. 2015). The focus of this contribution is the analysis of RGB image data after grass is cut and knowledge on harvested forage mass is demanded for managing purposes like improving fertilization schemes.

2 Study Area and Methods

2.1 The Rengen Grassland Experiment (RGE)

The study was conducted in 2014 on the Rengen Grassland Experiment (RGE) managed by the INRES (Institute of Crop Science and Resource Conservation) of the University of Bonn. The RGE is a long-term experiment established in 1941 in the Eifel Mountains in Germany (Rhineland-Palatinate, Germany, 50°13`N, 6°51`E). The design, floristic composition, soil properties and research foci are extensively described in previous publications (CHYTRÝ et al. 2009; HEJCMAN et al. 2007; SCHELLBERG et. al. 1999).

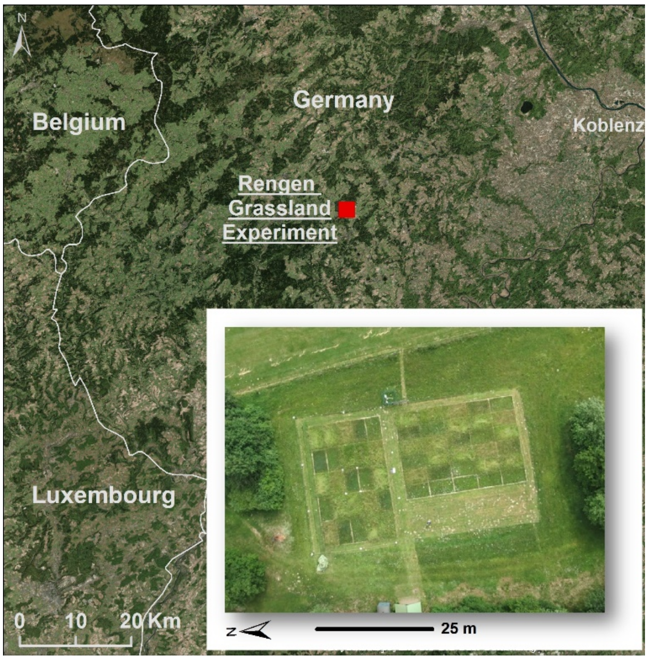

Fig. 1: Overview of the study area: The Rengen Grassland Experiment (data source: ESRI-Basemaps, Eurostat; Photo: G. Bareth)

The RGE is arranged in a randomized block design of five fertilizer treatments (Ca, CaN, CaNP, $CaNPK_2O$, $CaNPK_2SO_4$) with ten replicates per treatment on a plot size of 3×5 meter. The sward is cut twice per growing season, in early July and in mid-October. Due to the constant fertilizer application a distinct floristic composition per treatment and plot has evolved (CHYTRÝ et al. 2009).
For this study, one block was chosen for investigation (five replicates per treatment resulting in 25 plots). The pre-cut sampling date (t1) was on June 17th 2014 and the corresponding post-cut sampling date (t2) on July 6th 2014. From data of both sampling dates the RGBVI and the sward height (SH) was derived. Forage mass sampling was conducted in between on July 2nd 2014. Subsamples of forage mass from 6.5 m^2 of the 15 m^2 plots were taken and dry matter forage mass in kg per hectare was calculated. Additionally, rising plate meter (RPM) measurements were carried out with ten evenly distributed measurements per plot on June 23rd 2014. Forage mass sampling and RPM measurements were conducted by the INRES (HOLLBERG & SCHELLBERG 2017; BARETH et al. 2015).

2.2 The low-cost UAV system

In parallel to the RPM sampling campaigns image data was collected with a low-cost unmanned aerial vehicle (UAV), a DJI Phantom 2. The UAV was equipped with a consumer-grade RGB camera (Canon Powershot S110 with 12 MP) attached in nadir viewing position on a fixed camera mount being aware of image distortion due to UAV movements (Fig.2). The camera was equipped with a Canon Hack Development Kit (CHDK) to allow for continuous image acquisition. Shutter speed was set to 1/2000 with fixed aperture and ISO settings. For this analysis, we used the image data of June 17th because lodging already occurred on June 23rd.

Fig. 2: DJI Phantom 2 equipped with Canon Powershot 110 (BARETH et al. 2015)

The System was operated manually with a random flight pattern in about 20 m above ground level (AGL) to capture multiple overlapping images for Structure-from-Motion (SfM) processing with Agisoft Photoscan. Additionally, one overview image from about 40 m AGL was captured to minimize illumination effects when computing RGB-based vegetation indices for the whole area of interest. Evenly distributed ground control points for georeferencing were measured using a RTK-GPS.

2.3 Crop Surface Models (CSMs)

The concept of multitemporal crop surface models (CSM) was introduced by HOFFMEISTER et al. (2010) to derive plant height with terrestrial laser scanning. CSMs represent the increase in elevation due to plant growth of a certain crop in distinct phenological stages (Fig.3). To derive absolute plant height metrics, a DEM acquired at the beginning of the growing season shortly after sowing (t_0) is subtracted from the CSM of each succeeding sampling date (t_1, t_2, t_n) in a GIS environment. CSMs derived from UAV-based imagery are proofed to be a reliable estimator for biomass in barley as shown by BENDIG et al. (2014). Recently, the concept of CSMs was also successfully transferred to experimental grassland-sites to estimate sward height and forage mass (BARETH et al. 2015; POSSOCH et al. 2016; LUSSEM et al. 2017b).

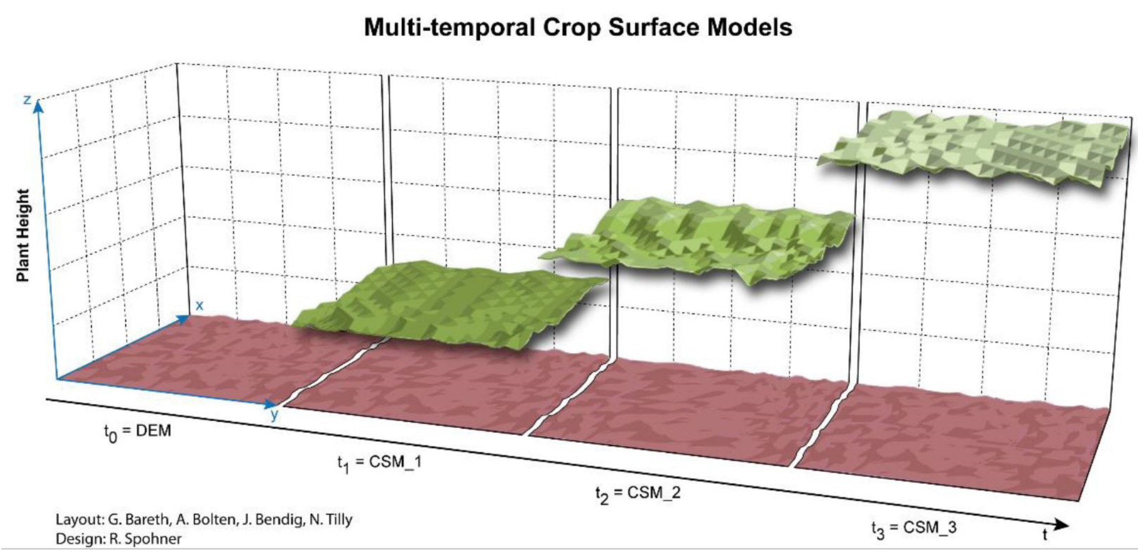

Fig. 3: Multi-temporal Crop Surfac Models (CSMs) (BENDIG et al. 2013)

2.4 Vegetation indices using the VIS domain

Vegetation indices (VIs) calculated from the visible (VIS) domain of the electromagnetic spectrum can be derived in high spatial resolution from UAV-based RGB images to assess vegetation-parameters, since they are sensitive to subtle changes in greenness by using the chlorophyll-absorption features in the red and blue part of the spectrum (HUNT et al. 2013). VIS-VIs have shown good results in estimating chlorophyll content (HUNT et al. 2011, 2013), biomass and LAI (GITELSON et al. 2003) or vegetation fraction (GITELSON et al. 2002). A recently introduced VIS-VI, the Red-Green-Blue Vegetation Index (RGBVI), performed moderately well to estimate biomass in barley (BENDIG et al. 2015).

$$RGBVI = ((R_G)^2 - (R_B*R_R)) / ((R_G)^2 + (R_B*R_R)) \quad (1)$$

with reflectance of the red (R), green (G) and blue (B) camera band.

Compared to the well-known NDVI the RGBVI showed less saturation effects in later growing stages for heterogenous grassland communities (LUSSEM et al. 2017a) and reached good correlations in grasslands (BARETH et al. 2015). Similar observations in terms of saturation effects for VIS-VIs are also shown by HUNT et al. (2013).

2.5 The multi-temporal Grassland Index (MtGI)

BARETH et al. (2015) introduced the Grassland Index (*Grass*I) as a combination of SH from CSMs and RGBVI (see equation 2) for each sampling date to differentiate the five RGE fertilization managements.

$$\mathit{Grass}\mathrm{I} = \mathrm{SH} + \mathrm{RGBVI} \qquad (2)$$

In contrast to the *Grass*I, the index proposed for grassland monitoring in this study, the Multi-temporal Grassland Index (MtGI), has a NDVI-like structure, but includes temporal changes in its equation.

$$\mathrm{MtGI} = ((\mathrm{SH}_{t1} + \mathrm{RGBVI}_{t1}) - (\mathrm{SH}_{t2} + \mathrm{RGBVI}_{t2})) \,/\, ((\mathrm{SH}_{t1} + \mathrm{RGBVI}_{t1}) + (\mathrm{SH}_{t2} + \mathrm{RGBVI}_{t2})) \qquad (3)$$

with sward height from crop surface models (SH), pre-cut (t_1) and post-cut (t_2) sampling date, and RGBVI see equation (1)

As can be seen in Fig. 4, the relationship between forage yield and appearance of greenness is inverse from t1 to t2. Plots with high fertilizer levels and therefore high sward height and forage yield (CaNP, CaNPKCl, $CaNPK_2SO_4$) appear less green in t2. In contrast, lower fertilizer levels with low sward heights (Ca, CaN) appear greener after the cut than the aforementioned plots. Based on these patterns, the MtGI was developed to incorporate the changes of structural and physiological information over time from RGBVI and CSM-based SH data.

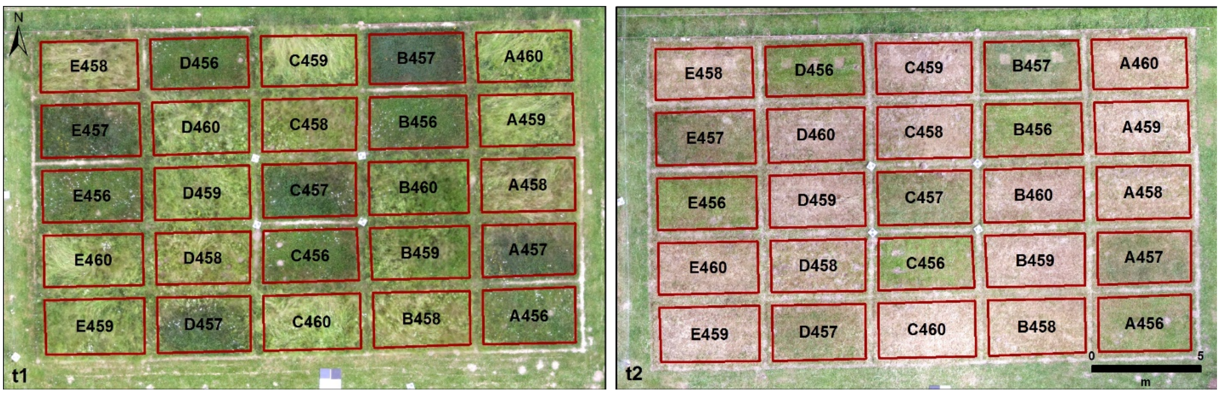

Fig. 4: t1: pre-cut (17.06.2014) & t2: post-cut (06.07.2014); capital letters indicate rows; treatment abbreviations: 456 (Ca); 457 (CaN); 458 (CaNP); 459 (CaNPKCl); 460 ($CaNPK_2SO_4$)

The RGBVI was calculated per pixel (see equation (1)) in a spatial resolution of 2 cm from the overview images of the RGE field experiment. For both sampling dates, digital surface models

were computed in the Structure from Motion (SfM) software Agisoft PhotoScan to derive sward height from CSMs (see Fig.3) (BENDIG et al. 2013; BENDIG et al. 2015).
Analysis of the UAV-based data as estimators of forage mass was conducted on the plot level. Therefore, the values of SH-CSM and RGBVI were averaged per plot using the analysis tool *Zonal Statistics as Table* in ArcGIS. Statistical analysis was computed in MS Excel with linear regression models for the above-mentioned estimators (SH-CSM, RGBVI, RPM, MtGI) of forage mass including the coefficient of determination (R^2).

3 Results

The spatial resolution of the CSMs for t1 and t2 and for the overview images of the RGE field experiment to calculate the RGBVI is 2 cm. The scatterplot in Fig. 5 (left) shows a strong correlation between the CSM-derived sward height (SH) and rising plate meter measurements (RPM) for compressed SH with a R^2 of 0.77. The RPM measurements are also averaged per plot from the ten individual measurements. However, the mean SH from CSMs per plot is higher compared to the values of the RPM. Fig. 5 (right) emphasis the strong correlation between forage mass and RPM measurements (R^2 = 0.85). The latter is well known in grassland sciences and proves the applicability of the method for the RGE.

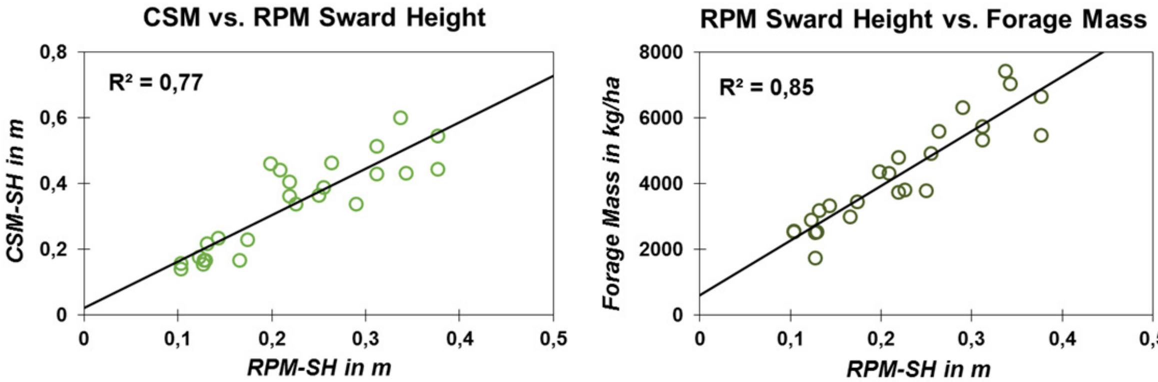

Fig. 5: left: Sward height (SH) from crop surface models (CSMs) in meter plotted against compressed SH from rising plate meter measurements (RPM) in meter for t1 (n=25). Right: Compressed SH from RPM measurements in meter plotted against dry matter forage mass in kg/ha (n=25)

In Fig. 6, the averaged plot data show a moderate correlation of the RGBVI for the pre-cut sampling date (t1, left) with forage mass and the trend is clearly visible. For the post-cut sampling date (t2, right), the t2 plot data with high forage mass yield are clustered around an RGBVI value of 0.19. The later indicates a kind of saturation of non-green values. However, a general trend is given resulting in a moderate to high R^2 of 0.7 which is higher than the pre-cut (t1) analysis.
The negative slope for t2 can be explained by the inversed greenness of the plots. Plots with high fertilizer input and high forage mass yield show higher values for the RGBVI (and higher SH) before the cut and lower values after the cut, because of the chlorophyll distribution and shading effects in taller grasses.

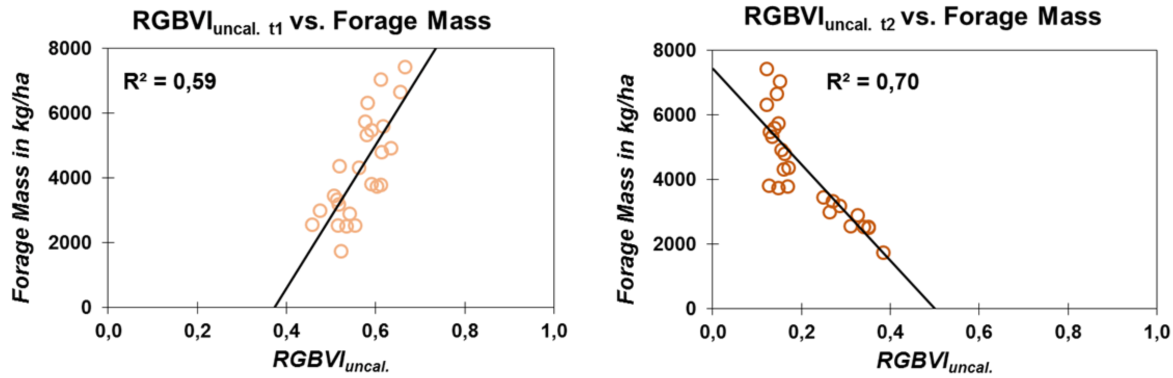

Fig. 6: left: scatterplot of RGBVI values for pre-cut (t1) against dry matter forage mass in kg/ha (n=25). right: scatterplot of RGBVI values for post-cut (t2) against dry matter forage mass in kg/ha (n=25)

In Fig. 7 (left), the averaged plot data of the Multi-temporal Grassland Index (MtGI) is plotted against forage mass (kg/ha) with a good correlation ($R^2 = 0.74$). However, the MtGI shows some severe saturation for higher forage yield, which is indicated by the clustering of data points between 0.6 and 0.8. A similar pattern can be observed when the MtGI is compared to the RPM measurements in Fig. 7 (right), although the R^2 value is slightly higher (0.78), the saturation is slightly weaker but still clearly visible.

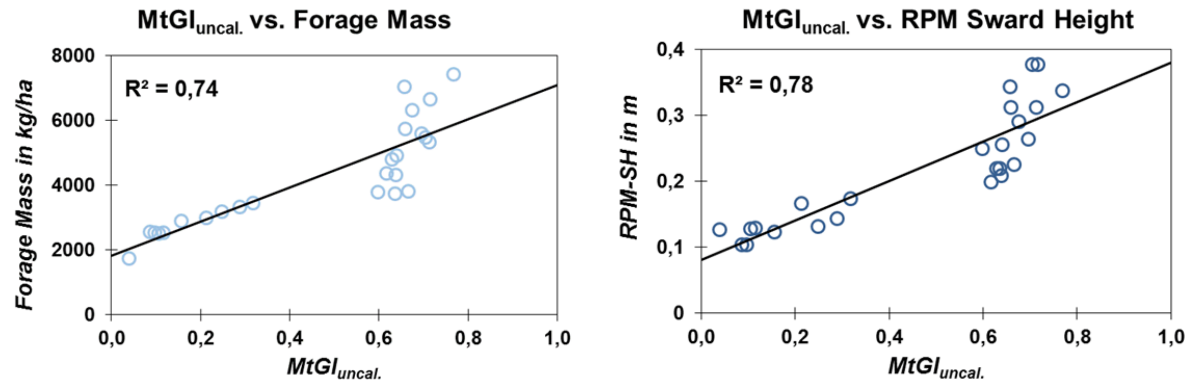

Fig. 7: left: scatterplot of MtGI values for pre-cut (t1) against dry matter forage mass in kg/ha (n=25). right: scatterplot of RGBVI values for post-cut (t2) against dry matter forage mass in kg/ha (n=25).

4 Discussion, Conclusion & Outlook

The newly introduced vegetation monitoring approach using a multi-temporal vegetation index, the Multi-temporal Grassland Index (MtGI), performed moderate to well. The innovative idea of the MtGI is the UAV-based grassland monitoring before (t1) and after (t2) cut with a low-cost system. The approach of remote sensing data acquisition after cut is rather unique and could lead to optimized grassland management strategies. However, the presented results are based only on one cutting date and consequently on one UAV data acquisition campaign before and one after

cut. The hypothesis of an inverse correlation pattern of the spectral data analysis (RGBVI) before and after cut is proofed in our contribution and bears a potential which should be further investigated. Especially when considering that the RGBVI data analysis is based on uncalibrated RGB images. In this context, Lussem et al. (2017a) proofed that empirical line corrected RGB images perform significantly better than uncalibrated (Bareth et al. 2015). Especially, the described saturation effects of the RGBVI were reduced which of course are also incorporated in the MtGI.
Compared to the results of the spectral analysis, the R^2 of the CSM-derived SH serving as a predictor for forage mass is significantly better, having a R^2 of 0.78, compared to the RGBVI ($R^2 = 0.59$). This fits well to other studies (Possoch et al. 2016; Bendig et al. 2015). However, while CSM-derived SH performs well to RPM data ($R^2 = 0.77$), RPM still is the strongest predictor for forage mass ($R^2 = 0.85$) in our study. Bareth et al. (2015) concluded that CSM-derived sward height correlated very well with RPM measurements considering data analysed for a whole growing season ($R^2 = 0.89$). This also supports the potential of further studies for multi-cut seasons. Finally, more sophisticated multivariate regression analysis should be investigated for the combination of CSM-derived SH with the RGBVI for grassland monitoring (Marshall and Thenkabail 2015; Bendig et al. 2015).

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