Investigating the Potential of a Newly Developed UAV-based VNIR/SWIR Imaging System for Forage Mass Monitoring

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Abstract

Remote sensing systems based on unmanned aerial vehicles (UAVs) are well suited for airborne monitoring of small to medium-sized farmland in agricultural applications. An imaging system is often used in the form of a multispectral multi-camera system to derive well-established vegetation indices (VIs) efficiently. This study investigates the potential of such a multi-camera system with a novel approach to extend spectral sensitivity from visible-to-near-infrared (VNIR) to short-wave infrared (SWIR) (400–1700 nm) for estimating forage mass from an aerial carrier platform. The system test was performed in a grassland fertilizer trial in Germany near Cologne in late July 2019. Within 37 min, a spectral response in four different wavelength bands in the NIR and SWIR range was acquired during two consecutive flights. Spectral image data were calibrated to reflectance using two different methods. The resulting reflectance data sets were processed to orthomosaics for each wavelength band. From these orthomosaics for both calibration methods, the four-band NIR/SWIR GnyLi VI and the two-band NIR/SWIR Normalized Ratio Index (NRI), were calculated. During both UAV flights, spectral ground truth data were recorded with a spectroradiometer on 12 plots in total for validation of camera-based spectral data. The camera and spectroradiometer data sets were directly compared in resulting reflectance and further analyzed with simple linear regression (SLR) models to predict dry matter (DM) yield. In the camera-based SLRs, the NRI performed best with R^2 of 0.73 and 0.75 (RMSE: 0.18 and 0.17) before the GnyLi with R^2 of 0.71 and 0.73 (RMSE: 0.19 and 0.18). These results clearly indicate the potential of the camera system for applications in forage mass monitoring.

Keywords Short-wave infrared (SWIR) · Unmanned aerial vehicle (UAV) · Precision agriculture · Forage mass · Grassland · Biomass

Zusammenfassung

Untersuchung des Potenzials eines neu entwickelten UAV-basierten VNIR/SWIR-Bildgebungssystems zum Monitoring von Futtermasse. Fernerkundungssensoren auf UAV-Plattformen eignen sich gut für das Monitoring von kleinen bis mittelgroßen landwirtschaftlichen Anbauflächen aus der Luft. Als bildgebende Systeme werden oft multispektrale Multikamerasysteme verwendet, um allgemein anerkannte Vegetationsindizes effizient abzuleiten. Diese Studie untersucht das Potenzial eines solchen Mehrkamerasystems mit einem neuartigen Ansatz zur Erweiterung der spektralen Empfindlichkeit vom sichtbaren und nah-infraroten Bereich (VNIR) bis zum kurzwelligeren Infrarot (SWIR) (400 – 1700 nm), um Futtermasse von einer luft-gestützten Trägerplattform aus abzuschätzen. Die Untersuchung wurde Ende Juli 2019 in einem Grünland-Düngeversuch in der Nähe von Köln durchgeführt. Innerhalb von 37 Minuten wurde bei zwei aufeinanderfolgenden Messflügen das spektrale Signal in vier verschiedenen Wellenlängenbändern im NIR- und SWIR-Bereich erfasst. Die spektralen Bilddaten wurden mit zwei verschiedenen Methoden in Reflektanzwerte überführt. Die resultierenden Reflektanzdatensätze wurden für jedes Wellenlängenband zu Orthomosaiken verarbeitet. Aus diesen Orthomosaiken wurden für beide Kalibrierverfahren der Vier-Band NIR/SWIR GnyLi Index und der Zwei-Band NIR/SWIR Normalized Ratio Index (NRI) berechnet. Während beider UAV-Flüge wurden zur Validierung der kamerabasierten Spektraldaten mit einem Spektorradiometer auf insgesamt 12

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Parzellen des Versuchsfeldes Ground-Truth Daten aufgezeichnet. Die Kamera- und Spektralradiometer-Datensätze wurden bezüglich der resultierenden Reflektanz direkt verglichen und mit einfachen linearen Regressionsmodellen (simple linear regression, SLR) weiter analysiert, um den Ertrag an Trockenmasse abzuschätzen. Bei den kamerabasierten SLRs schnitt der NRI mit einem R^2 von 0,73 und 0,75 (RMSE: 0,18 und 0,17) am besten ab, vor dem GnyLi mit R^2 von 0,71 und 0,73 (RMSE: 0,19 und 0,18). Diese Ergebnisse zeigen deutlich das Potenzial des Kamerasystems zum Monitoring der Futtermasse.

1 Introduction

Grassland ecosystems cover almost 30 % of the total land area and approx. 70 % of the global agricultural land is managed grasslands (Boval and Dixon 2012; Gibson 2009). Grasslands are critical “as a feed source for livestock, as a habitat for wildlife, for environmental protection and for the in-situ conservation of plant genetic resources” (Suttie et al. 2005). Furthermore, they are of high cultural and economic value (Nelson et al. 2017), comprising pastureland, rangeland, and cropland for forage production such as grass, silage, or hay (Nelson et al. 2017), and provide the base for meat, dairy, and wool production.

In managed grasslands, pastures, rangelands, and meadows, the information on sward height and growth for forage mass estimates is crucial for management decisions (Evans and Jones 1958; Higgins et al. 2019). Consequently, the approaches for non-destructive estimation of spatial forage mass production were investigated for decades (Santillan et al. 1979; Bareth et al. 2015; Legg and Bradley 2020). In the 1960s, the development of so-called disk-meters started (Castle 1976) and led to the development of Rising Plate Meters (RPMs) (Earle and McGowan 1979), which are measuring compressed sward height as an estimator for forage mass (Sanderson et al. 2001). Such systems in modern electromechanical versions are still used by farmers and provide robust and reliable estimates. Newer technologies to measure sward height are rapid pasture meters (King et al. 2010) using light beams measurements as well as ultrasonic devices (Fricke and Wachendorf 2013).

A completely different approach for nondestructive estimation of forage mass is optical remote sensing. A wide range of imaging sensors for different carrier systems (mobile, aerial, and satellite) are available, providing multi- and hyperspectral image data in the visible and near-infrared (VNIR) domain (approx. 300–1000 nm). Portz et al. (2017), Näsi et al. (2018), and Capolupo et al. (2015) have successfully investigated such optical approaches. In this context, portable field spectroradiometer studies are of essential importance for identifying the potential of significant spectral domains and for evaluating remote sensing data (Hollberg and Schellberg 2017; Lussem et al. 2019). In the past 15 years, numerous studies emerged where unmanned aerial vehicles (UAVs)

have been used as a carrying platform for miniaturized multi- and hyperspectral sensors (Hardin and Jackson 2005; Rango et al. 2006; Berni et al. 2009; Hunt et al. 2010; Aasen et al. 2015; Geipel et al. 2016). Such aerial mapping systems or field spectroradiometer measurements were also applied for forage mass monitoring. Lussem et al. (2019) reported varying performances of selected VNIR VIs as estimators for dry matter (DM) yield with R^2 ranging from 0.32 to 0.86. Viljanen et al. (2018) derived similar VIs from UAV-based image acquisition. The latter study described Pearson Correlation Coefficients (PCC) for DM yield ranging from 0.3 to 0.9. Capolupo et al. (2015) acquired image data with a VNIR hyperspectral UAV sensor system. The results of regression analyses against DM yield varied in R^2 values between 0.36 and 0.57. For crop monitoring, Koppe et al. (2012) and Gnyp et al. (2014b) proofed the promising potential of reflectance features in the shortwave-infrared (SWIR) for biomass monitoring of winter wheat using a two-band NIR/SWIR-based Normalized Ratio Index (NRI) and the four-band NIR/SWIR GnyLi vegetation index. In the studies by Gnyp et al. (2014a), Koppe et al. (2010), Koppe et al. (2012), Bendig et al. (2015), and Tilly et al. (2015), the NRI and GnyLi outperformed the VIs using VNIR wavelengths. Therefore, a UAV-based multi-camera imaging system covering these VNIR/SWIR bands is demanded to efficiently evaluate the potential of the VNIR/SWIR range for grassland monitoring. To the authors' knowledge, UAV-borne NIR/SWIR data of such a camera system have not yet been investigated for grassland monitoring.

In a previous study, the authors have developed a novel prototype of a UAV-based remote sensing multispectral multi-camera system. The centerpiece of the system consists of two compact scientific camera modules, based on indium gallium arsenide (InGaAs) sensors, to capture spectral image data from the VNIR and SWIR spectral range (Jenal et al. 2019). These camera modules provide a higher spectral sensitivity within the 400–1700 nm wavelength range, made possible by an additional etching step during the manufacturing process (Martin 2015). Thus, vegetation indices can be derived not only within the NIR/SWIR spectral range but also in additional combinations within the entire VNIR and SWIR wavelength range. Suitable hybrid bandpass filters select the required spectral bands for vegetation indices out of the incoming light. These filters are mounted via c-mount flanges developed explicitly for this particular system. Each

Fig. 1 System overview of the novel, modular-designed VNIR/SWIR multispectral multi-camera 2D imaging prototype for UAV-based remote sensing applications (modified after Jenal et al. 2019)

bandpass filter used with the camera system is installed into a separate interchangeable flange. This filter assembly can be mounted in the optical path of each camera, between the prime lens and sensor, to achieve the best possible image data quality. This flange allows quick as well as repeatable filter changes and adapts the filter to the optical system. In Fig. 1, the newly introduced imaging sensor system for UAVs is shown (Jenal et al. 2019). The modular camera system divides into two parts so that it can be easily integrated into many different airborne carrier platforms, especially into UAVs. The Spectral Camera Unit (SCU) consists of two InGaAs cameras, while the Spectral Management Unit (SMU) combines the control and storing unit. For the spectral measurements performed in this study, the dual-camera system was equipped with four bandpass filters, for the NIR and SWIR spectral range, to derive the NRI and GnyLi VIs mentioned above. Since the prototype of the camera system currently consists of only two InGaAs-based cameras arranged in parallel, more complex VIs, which require more than two wavelength bands, have to be composed of several consecutive flights with the shortest possible time delay.

According to Honkavaara et al. (2016), Camino et al. (2018), and Aasen and Bareth (2018), the VNIR/SWIR domain provides an unexploited potential for UAV-based monitoring of vegetation. Therefore, the overall aim of this study is to evaluate the potential of the newly developed VNIR/SWIR multispectral multi-camera 2D imager for grassland monitoring, as described by Jenal et al. (2019). A first UAV-borne data acquisition campaign was carried out on a chessboard experiment on permanent grassland near Cologne, Germany, in July 2019. As a result, spectral data were acquired by the camera system in the NIR/SWIR spectral range as well as narrow-band hyperspectral ground truth data from a portable field spectroradiometer. Moreover,

destructively measured DM yield data were obtained. With these data sets the following main objectives of this study are (1) to validate the spectral performance of the UAV-mounted multi-camera sensor system in-situ, (2) to compare UAV-derived NIR/SWIR image data with hyperspectral ground truth measurements using a portable field spectroradiometer, (3) to evaluate well-established VNIR VIs using the spectroradiometer data, and (4) performing simple linear regression analyses (SLR) of destructively measured DM yield against UAV-derived NIR/SWIR VIs and the equivalent spectroradiometer VNIR/SWIR VIs.

2 Study Site and Methods

2.1 Study Site

This study was based on data acquired on a grassland field trial in Germany. The permanent grassland site is located in Neunkirchen-Seelscheid (Bergisches Land region, North Rhine-Westphalia), about 30 km southeast of Cologne. The mean annual temperature is 10 °C, and the mean annual precipitation about 800 mm. The experimental field was established in March 2017 on a conventionally managed permanent grassland. The field trial comprised three nitrogen (N) fertilizer application levels (50, 100, 150 kg N ha⁻¹) and one control with no fertilizer applied at all, ending up in four treatments. Each treatment comprised 39 replicates, resulting in 156 plots systematically arranged in a chessboard pattern (see Fig. 2). Each plot covered an area of 6 × 6 m². The experimental field was managed as a three-cut system. The first cut was harvested in May, the second in July, and the third in October, similar to local farming practice.

2.2 Yield Reference Data/Biomass Sampling

For yield reference data, biomass samples were collected on August 5th, 2019. A conventional lawn mower was used to harvest a 0.54 × 5.46 m² strip of standing biomass from each of the 156 plots. The fresh biomass samples were weighed directly, and from that, subsamples were taken for DM calculation. Subsamples were dried in a forced-air dryer to constant weight for 3 days at 65 °C. Subsequently, weights of dried subsamples were used to calculate dry above-ground biomass yield per hectare (t ha⁻¹).

2.3 Spectroradiometer Ground Truth Measurements

The spectral ground truth data were measured with an ASD FieldSpec3 spectroradiometer (Malvern Panalytical Ltd,

Fig. 2 Location map and additional information of the experimental site in Neunkirchen-Seelscheid

Table 1 Vegetation indices used in this study. Indices a-l were applied to the spectral ground truth data of the ASD Fieldspec3 spectroradiometer. Indices (k) and (l) were also applied to the spectral image data of the camera

	Names	Equations	References
(a)	NDVI	$\frac{R_{800} - R_{670}}{R_{800} + R_{670}}$	Rouse et al. (1974)
(b)	RDVI	$\frac{(R_{798} - R_{670})}{(\sqrt{R_{798} + R_{670}})}$	Roujean and Breon (1995)
(c)	OSAVI	$\frac{1.16 \times (R_{800} - R_{670})}{R_{800} + R_{670} + 0.16}$	Rondeaux et al. (1996)
(d)	REIP	$700 + 40 \times \frac{\frac{R_{670} + R_{780}}{2} - R_{700}}{R_{740} + R_{700}}$	Guyot and Baret (1988)
(e)	NDREI	$\frac{R_{790} - R_{720}}{R_{790} + R_{720}}$	Gitelson and Merzlyak (1994)
(f)	MTCI	$\frac{R_{754} - R_{709}}{R_{709} - R_{681}}$	Dash and Curran (2004)
(g)	CI-Green	$(R_{780} - R_{550}) - 1$	Gitelson et al. (2003)
(h)	RVI	$\frac{R_{800}}{R_{670}}$	Pearson and Miller (1972)
(i)	PRI	$\frac{R_{512} - R_{531}}{R_{512} + R_{531}}$	Hernández-Clemente et al. (2011)
(j)	MSAVI	$\frac{\left(2 \times R_{800} + 1 - \sqrt{2 \times R_{800} + 1}\right)^2 - 8 \times (R_{800} - R_{670})}{2}$	Qi et al. (1994)
(k)	GnyLi	$\frac{R_{910} \times R_{1100} - R_{980} \times R_{1200}}{R_{910} \times R_{1100} + R_{980} \times R_{1200}}$	Gnyp et al. (2014b)
(l)	NRI	$\frac{R_{910} - R_{1200}}{R_{910} + R_{1200}}$	Koppe et al. (2010)

Malvern, United Kingdom). Three (No. 15, 20, and 26, see Fig. 2) out of the overall 39 replicates, evenly distributed across the experimental site, were selected for spectral ground-truthing. Spectral field measurements were conducted between 10:58 a.m. and 12:05 p.m. on the 12 plots of these replicates. In each plot, between 13 and 17 spectral measurements were taken to cover the complete plot area. For each spectrum obtained, ten spectra were averaged. Before starting measurements on individual plots, white (Zenith Lite™ panel) and dark reference measurements were obtained. The resulting raw spectra were transformed to reflectance and corrected for sensor offset (splice correction) using the ASD-software IndicoPro v5.0. Subsequently, the spectra were smoothed using a Savitzky-Golay filter implemented in the R package “prospectr” (Stevens and

Ramirez-Lopez 2013, R package version 0.2.0). The arithmetic mean of all spectra recorded in a plot was calculated. The averaged spectra were then used to calculate VIs in the VNIR/SWIR range (see Table 1). The vegetation indices listed in Table 1 were selected based on previous studies on biomass estimation in crops and grassland studies (Koppe et al. 2010; Gnyp et al. 2014a; Tilly et al. 2015; Capolupo et al. 2015; Viljanen et al. 2018; Näsi et al. 2018; Lussem et al. 2019). The spectral data recorded by the ASD FieldSpec3 spectroradiometer, as well as the derived vegetation indices, are marked *ASD* in the subsequent sections.

Fig. 3 **a** Pre-flight image of the white calibration panel and the marked area (red circle) that is used for reflectance calibration during post-processing. **b** Reflectance data, provided by the manufacturer, of the spectrally precisely characterized lambertian Zenith™ polymer white panel with 95% reflectance. **c** In-flight image of the six differ-

ently graded grey panels and the marked areas (red squares), which are used for reflectance calibration with the empirical line method in post-processing. **d** Reflectance values of the six grey panels measured by an ASD FieldSpec3 spectroradiometer

2.4 Image Data Acquisition

With the first flight starting at 11:03 a.m., spectral image data were acquired with the above-described camera system around noon under clear sky conditions on July 23rd, 2019. The modular system was mounted on an MK S612 Oktokopter (HiSystems GmbH, Moormerland, Germany), with the spectral camera unit mounted in the gimbal and the control unit on the rigid frame of the UAV. Within 37 min, two UAV flights (approx. 7 min each) were performed in short succession. After the first flight, the filter arrangement was changed from 910 to 1100 nm and 980 to 1200 nm. When changing filters in the field, consistent image quality has to be ensured throughout the flights. Therefore, each bandpass filter was installed in its own filter flange, which was matched to the entire optical system. Moreover, these filter mounts have been mechanically designed to be always positioned in the same way as during initial flat-field calibration in the laboratory (see Jenal et al. 2019). A series of calibration images from a spectrally precisely characterized Zenith™ polymer white panel with 95% lambertian reflectance as well as additional dark images were taken before each flight (see Fig. 3a, b). This correction data was used in post-processing for a one-point calibration of the image digital numbers (DNs) to reflectance values and is referred to as the White-Panel-Method, abbreviated *WPM*. Besides, six differently graded and also spectrally well-characterized $80 \times 80 \text{ cm}^2$ near-lambertian grey panels were placed next to the test site. These greyscale panels (0, 10, 25, 50, 75 and 100 % black shading) were then captured in-flight and were used, in addition to the White-Panel-Method, for reflectance calibration of the DNs according to the empirical line method published by Smith and Milton (1999). The reflectance data, as well as the vegetation indices derived by the empirical line method, are given the suffix *ELM* in the following. The flight duration was about 7 min each and resulted in around 1000 images per channel with a constant flight altitude of 30 m above ground level (AGL). The camera system's aperture and exposure settings were kept constant during both flights of the survey campaign. In combination with the lenses used, the calculated ground sampling distance (GSD) resulted in approx. 0.04 m. To georeference the data thereafter, fifteen ground control points were evenly distributed across the experimental site (see Fig. 2). Then their exact geolocation was measured with high accuracy using a Real-Time Kinematic Differential Global Positioning System (RTK-DGPS) receiver (Topcon GR5).

2.5 Image Data Processing

The image data of each of the four spectral bands were individually flat-field corrected. To this end, accurate flat-field measurements at an integrating sphere and measurements for

dark signal compensation in a climatic chamber have been performed in advance for accurate sensor characterization (Jenal et al. 2019). These preprocessed images were then converted from at-sensor radiance into at-surface reflectance values. This subsequent transformation was carried out using two different methods, based on the empirical line method described by Smith and Milton (1999) and empirically proven by Baugh and Groeneveld (2008). In this study, simplified empirical line procedures for UAV-based imaging sensors, derived by Wang and Myint (2015) and Iqbal et al. (2018), were applied. First, pre-flight calibration data were taken from a white calibration target for a one-point calibration, which is the simplest form of the empirical line method (see Smith and Milton 1999). Figure 3a shows one of 20 white calibration images, which were acquired for the WPM immediately before a flight and averaged afterward. The red circular marking encloses the area of the image that was used for reflectance calibration of the previously flat-fielded image data. For this reason, the target must also be positioned as centrally as possible in both camera images before acquiring the images, which can be done using the control software of the SCU. Secondly, a calibration was performed by in-flight measurements of six differently shaded grey targets for a more sophisticated approach of the empirical line method. Figure 3c shows one of the calibration images with the included greyscale targets during a flyover (first flight, 910 nm channel) as an example. Each red box in the zoomed view shows the pixel locations that were extracted with the OpenCV (Bradski 2000) *imcrop tool* to determine the average digital number (DN) for every grey target. For each target, approx. 90 pixels were averaged. The mean image DN of each calibration panel was then plotted against the mean reflectance of the calibration panels determined by reference measurements with an ASD FieldSpec3 spectroradiometer (see Fig. 3d) in a scatter plot. Linear regression was then applied to determine the calibration equation in the form of (see Iqbal et al. 2018):

$$\text{Reflectance} = \text{slope} \times \text{DN} + \text{intercept.} \quad (1)$$

Both workflows were processed with the Python programming language using IPython (Perez and Granger 2007) in a JupyterLab (Kluyver et al. 2016) environment. Both reflectance image data sets of each flight were imported separately in the Structure-from-Motion (SfM) software Metashape (Agisoft Ltd, St. Petersburg, Russia, v 1.6.2) with the *rigid camera rig* option to process a two-layer georeferenced orthomosaic per flight and for each calibration method. Therefore, corresponding metadata was added to the individual image data sets of each flight via the command-line application ExifTool (Harvey 2019, v 11.66). Due to a low image resolution of 640×512 pixels, the accuracy setting *Highest* had to be selected for successful image alignment of

Fig. 4 GnyLi VI (WPM calibration) orthomosaic derived from the four waveband orthomosaics processed from the camera system’s spectral image data

the two layers. This setting forces the algorithm to upscale the image size by a factor of 4. For the further processing steps, the individual settings have been switched to *Medium* mode. After the SfM process, the resulting two-layer orthomosaics of the WPM and the ELM calibration were used to calculate the orthomosaics for the GnyLi (see Fig. 4) and the NRI VIs of both calibration methods. The applied equations for both indices are listed in Table 1(k) and (l). Subsequently, with a total of six orthomosaics per calibration method, zonal statistics were derived. The mean and the standard deviation were calculated from the raster data using vector data of the individual plot positions. Zonal statistics were performed with the Python packages *geopandas* (Jordahl et al. 2020), *rasterstats*, and *rasterio* in JupyterLab.

2.6 Spectral Data Analysis

Well-established vegetation indices from the VNIR/SWIR range (see Table 1) were derived from the narrow-band spectral ground truth measurements of the ASD FieldSpec3 spectroradiometer to compare their prediction quality in simple linear regressions (SLR) for dry matter (DM) yield with that of camera-based NIR/SWIR VIs. To evaluate the spectral properties of the VNIR/SWIR camera system, the reflectance values of the individual spectral bands, as well as the

two VIs GnyLi and NRI, were directly compared with the corresponding ASD values. Additionally, SLR analyses were performed to determine whether the two vegetation indices

Fig. 5 a–d The linear relationship between mean DN of the target area in the cameras’ calibration images and mean reflectance of the calibration panels measured by an ASD FieldSpec3 spectroradiometer for all four wavelength bands of the VNIR/SWIR camera system. Each data point represents one of the six calibration targets. X- and y-axes are shared among graphs ($p < 0.0001$)

Table 2 Summarized statistics for the reflectance prediction equation derived from the empirical line method ($p < 0.0001$)

Channel	Prediction equation	R^2	RMSE
910 nm	$y = 0.0002x - 0.1126$	0.9997	0.0035
1100 nm	$y = 0.0001x - 0.1407$	0.9998	0.0021
980 nm	$y = 0.0001x - 0.1012$	1.0000	0.0012
1200 nm	$y = 0.0001x - 0.1419$	0.9997	0.0025

Table 3 Summarized statistics for the linear regression models of the twelve VNIR VIs and the DM yield ($p < 0.001$)

	VI	Equations	R^2	RMSE
(a)	NDVI	$y = 6.98x - 5.11$	0.86	0.12
(b)	RDVI	$y = 6.68x - 3.03$	0.94	0.08
(c)	OSAVI	$y = 6.48x - 3.92$	0.92	0.09
(d)	REIP	$y = 0.12x - 82.28$	0.81	0.14
(e)	NDREI	$y = 4.85x - 0.92$	0.79	0.15
(f)	MTCI	$y = 0.43x - 0.43$	0.77	0.16
(g)	CI-Green	$y = 7.2x + 5.5$	0.93	0.09
(h)	RVI	$y = 0.07x - 0.16$	0.88	0.11
(i)	PRI	$y = -13.26x - 2.47$	0.59	0.21
(j)	MSAVI	$y = -2x - 2.08$	0.93	0.09
(k)	GnyLi	$y = 11.62x - 0.38$	0.90	0.10
(l)	NRI	$y = 10.26x + 0.29$	0.83	0.13

GnyLi and NRI, obtained from the camera system, could potentially provide a reliable prediction of DM yield. These analyses were carried out in two ways. First, the analyses were performed with the WPM, ELM, and ASD data sets for the twelve spectral ground truth plots of replicates 15, 20, and 26. Additionally, only the WPM and ELM camera-based VIs GnyLi and NRI were analyzed in another SLR with the DM yield data of all 156 plots since no ASD spectral ground truth data were available for all plots. Quality measures, such as the coefficient of determination (R^2) and the root-mean-square error (RMSE), were determined for all SLR analyses.

3 Results

3.1 Reflectance Calibration

The spectral image data acquired during both flights were flat-field corrected and then converted from at-sensor radiance into at-surface reflectance values based on the empirical line method. This was done using the WPM and the ELM procedure described in Sect. 2.5. Figure 5 displays the scatter plots with the linear relationship between the mean DN_s of the camera data and the reflectance of the calibration panels for all four wavelength bands. Table 2 lists the calibration

equations for all four wavelength channels and the quality measures derived from the applied ELM of the six calibration panels. The 910 nm band exhibits the highest RMSE of 0.0035. The three remaining bands were below this value, with 980 nm having the lowest RMSE of 0.0012.

3.2 ASD-based VIs vs. DM Yield

Vegetation indices were derived according to Table 1 based on ASD data. Each VI data set of the twelve spectrally measured plots was correlated with DM yield data in an SLR analysis. Table 3 concisely summarizes the statistical parameters of this analysis.

As shown in Table 3, the VIs used for the SLR analyses, except for the PRI, consistently show a good to an excellent level of accuracy (R^2 : 0.77–0.94) for the estimation of DM yield. Figure 6 displays the twelve scatter plots of the ASD derived VIs (see Table 1) against the DM yield. The performance of the two ASD VIs GnyLi and NRI was very good (R^2 of 0.90 and 0.83). The results of both VIs are compared with the camera-based WPM and ELM VIs and displayed below.

3.3 Direct Comparison: Camera vs. ASD Data

Figure 7a–d directly compares the calibrated reflectance data recorded by the camera system (WPM, ELM) per plot to the corresponding ASD reflectance data. As can be seen in Fig. 7, the three reflectance values for each plot differed only slightly. Averaged over all plots of a measured wavelength, the mean relative difference of the WPM values differ from the reference values of the ASD by 5.72 % and the mean relative difference of the ELM values by only 3.28 %. A clear pattern of the two methods of over- or underestimating the reference values was not apparent. The standard deviation (SD) of the mean ASD reflectance data was lower (0.013–0.044) as compared to WPM (0.024–0.059) and ELM (0.030–0.073) data. This can be explained by the higher spatial resolution of the image data compared to the point measurements of the spectroradiometer. From the VNIR/SWIR image data, approx. 17,200 pixel values were averaged per plot. From the ASD, between 13 and 17 spectra were averaged per plot, each providing a footprint of about 0.6 m. Based on the processed GnyLi and NRI orthomosaics, the mean values for both indices of the WPM and ELM were calculated pixel-wise per plot of each replicate via zonal statistics. These data were then compared for each plot of the three replicates with the indices calculated from the ASD data. Figure 7 shows a comparison of three modalities per plot of the three spectral reference replicates for the GnyLi (Fig. 7e) and the NRI (Fig. 7f). With the GnyLi index, the three values per plot were relatively close together. A mean relative difference of 11% for the WPM and 10% for

Fig. 6 a–l Scatter plots of the individual VIs listed in Table 1 derived from the ASD data and the DM yield. Regression Lines and quality measures from an SLR are added ($p < 0.001$)

the ELM method from the ASD reference value was found. For the NRI, the WPM method led to a significant difference of more than 63%. The ELM method reveals an average relative difference of 37% to the ASD derived indices. Both GnyLi data sets (WPM, ELM) of the camera system show that there was no clear trend in under- or overestimating the ASD-based VI values. However, it is also visible that NRI WPM and ELM values permanently and indefinitely underestimated ASD reference values.

3.4 DM Yield Estimation: Camera and ASD VIs

SLR analyses were performed from the three GnyLi and NRI spectral data sets (WPM, ELM, and ASD) against the DM yield data derived from destructive biomass sampling. Table 4 lists the predictor equations and the statistical results R² and RMSE of the six regression models. Figure 8 shows

the six scatter plots with regression lines as well as R² and the RMSE as performance measures.

As can be seen in Table 4, the two indices based on the ASD data provided a higher R² (between 23 and 28% compared to the GnyLi and 6–10% to the NRI) and a lower RMSE compared to camera-based indices. When comparing the two calibration methods of the camera-based indices with each other, the WPM shows slightly better values for R² and RMSE, both about 6%, compared to the ELM method.

3.5 DM Yield Estimation: Camera VIs - All Plots

The GnyLi and the NRI VIs derived from camera data (WPM and ELM) of all 156 plots were correlated with the DM yield via SLR. Figure 9 shows the four resulting scatter plots with regression lines and the corresponding statistical

Fig. 7 a–d Direct comparison of the spectral ground truth data of the ASD and the spectral camera reflectance data (WPM, ELM) for each plot of the three replicates and wavelength band. Error bars represent standard deviation. Comparison of the (e) GnyLi VI and the (f)

NRI for the two calibration methods (WPM and ELM) of the camera data and the spectral ground truth ASD data for each plot of the three measured replicates. The y-axes represent the individual plot number of the three replicates and are shared among the subplots

quality characteristics R^2 and RMSE. As described in Sect. 2, spectral ground truth data are only available for three replicates (12 plots). Therefore, the two indices calculated on the ASD data are not applicable here. However, these plots are marked separately in Fig. 9a–d and are referred to as “spectral plots” in the respective legend.

Table 5 summarizes this information. Compared with the results for R^2 and the RMSE from Table 4, the R^2 for the GnyLi indices performed better, albeit only slightly. For the NRI, however, they have declined to a minor extent.

Table 4 Summarized statistics of simple linear regression models of the two NIR/SWIR VIs GnyLi and NRI (WPM and ELM camera data as well as from ASD data) against DM yield for the twelve plots of the three replicates ($p < 0.001$)

VI	Equations	R^2	RMSE	n
GnyLi (ELM)	$y = 10.48x - 0.24$	0.70	0.18	12
GnyLi (WPM)	$y = 14.26x - 0.55$	0.72	0.17	12
GnyLi (ASD)	$y = 11.62x - 0.38$	0.90	0.10	12
NRI (ELM)	$y = 10.77x + 0.34$	0.75	0.16	12
NRI (WPM)	$y = 13.91x + 0.57$	0.77	0.16	12
NRI (ASD)	$y = 10.26x + 0.29$	0.83	0.13	12

4 Discussion

The study aimed to validate the spectral performance and to investigate NIR/SWIR image data of a newly developed VNIR/SWIR multi-camera prototype for forage mass monitoring. For this purpose, spectral data were acquired on an experimental grassland site near Cologne, Germany, under clear sky conditions in July 2019. The forage mass expressed in dry matter (DM) yield used in the study was obtained by destructive biomass sampling 14 days after the flight date. The weather situation during this period was warm and dry, with occasional short rainfall, so that despite the two-week offset, it can be assumed that the additional growth is still representative of the date of flight and does not have a significant effect on the analyses.

4.1 Direct Comparison of Spectral Data Sets

The acquired spectral image data were compared to near-ground data of a portable field spectroradiometer. By directly comparing the camera reflectance data with the ASD data, a clear pattern of under- or overestimation could not be detected. A significant difference in the

Fig. 8 Simple linear regression ($p < 0.001$) (a)–(c) for DM yield versus GnyLi VI derived from two different camera calibration methods (WPM, ELM) with ASD data and d–f for measured DM yield and NRI derived from two different camera calibration methods (WPM, ELM) and the ASD data. Y-axes are shared among graphs

standard deviation (SD) of the individual reflectance values per plot could be observed. The SD of the ASD values is relatively low (ASD: 0.013–0.044) compared to the UAV-derived reflectance data (approx. factor 1.5–2, WPM: 0.024–0.059, ELM: 0.030–0.073). One reason could be that for each plot, 13–17 ASD spectra were captured and averaged in contrast to approx. 17,200 spectral pixels for the mean camera reflectance values (WPM, ELM) per plot. The overall spectral performance compared to the ASD data and the very high correlation to greyscale panels of $R^2 > 0.99$ for the empirical line method are considered to be very good and prove the suitable application of the newly introduced VNIR/SWIR imaging system for UAV-based vegetation monitoring (see Jenal et al. 2019).

4.2 Forage Mass Estimation

For the estimation of forage mass, three approaches were investigated for the spectral data evaluation.

- (i) Narrow-band VIs (see Table 1) were calculated from the ASD FieldSpec3 recorded spectra for selected

plots and evaluated against (DM) yield using simple linear regression analysis (SLR). The results listed in Table 3 show a good to excellent performance with R^2 from 0.59 to 0.94 and RMSE from 0.08 to 0.21 t ha⁻¹ for the narrow-band VIs as a predictor of biomass. In contrast to studies in crops, the two investigated NIR/SWIR VIs do not outperform VNIR VIs (Gnyp et al. 2014a; Tilly et al. 2015). However, both NIR/SWIR VIs, the GnyLi and NRI, show very high R^2 values of 0.83 and 0.9, respectively, using the ASD spectral data. In their studies, Viljanen et al. (2018) and Näsi et al. (2018) used, amongst more sophisticated methods, the SLR in biomass estimation of grass, based on spectral VNIR data acquired with a drone-based FPI camera. With derived VIs similar to our study, the former reached comparable levels in Pearson Correlation Coefficients (PCC) varying from 0.23 to 0.95 throughout four flight dates. The latter reached a PCC of 0.79. Lussem et al. (2019) used narrow-band VIs based on ASD data as a reference and observed that the spectroradiometer VIs compared to camera-based ones, performed better—having cross-validation R^2 between 0.44 and 0.87 for bivariate linear regression. Similar results can be described from this study using the spectral data of the UAV-borne VNIR/SWIR imaging system.

- (ii) The estimations of forage mass via the simple linear regression analyses for all three spectral data sets (WPM, ELM, ASD) of the twelve selected plots performed well. For the camera-based VIs, the NRI data with R^2 of 0.75 for the ELM and R^2 of 0.77 for WPM performed better compared to the GnyLi data (ELM R^2 : 0.70 and WPM R^2 : 0.72). As expected, the SLR analyses based on the spectral ground truth ASD-derived GnyLi (R^2 : 0.9) and NRI (R^2 of 0.83) indices outperformed the respective camera-based VIs. Comparing the two approaches WPM and ELM for reflectance calibration, the WPM performed slightly better but did not outperform the ELM. Both methods have to be investigated further for the robustness of calibration in future and multi-temporal campaigns.
- (iii) The SLR analyses results for the spectral camera data of all 156 plots show robust and good results with R^2 of 0.73 (ELM) and 0.75 (WPM) for the NRI, which means a non-significant decline in performance. The GnyLi, however, showed slightly better accuracies—but also non-significant ones—with a R^2 of 0.71 (ELM) and 0.73 (WPM) compared to the evaluation method (ii). Schut and Ketelaars (2003) applied a hyperspectral line scanner (404–700 nm) with 5 nm spectral resolution on grass swards and reported similar R^2 of 0.59 and for an exponential function 0.82. The latter usually performs better for multi-

Fig. 9 Simple linear regression analysis of the NRI: **a** WPM and **b** ELM and of the GnyLi VI: **c** WPM and **d** ELM with DMY; for all 156 plots of the experimental site ($p < 0.001$ for all). Markers of

plots with available ASD data (called “spectral plots”, see legend) are highlighted with a green circle

temporal data sets, which is also reported by Gny et al. (2014b) for the GnyLi. The authors document R^2 between 0.8 and 0.85 for a multi-temporal and multi-experiments study on winter wheat. Similar results have been presented by Tilly et al. (2015) and Bendig et al. (2015) for winter barley, the NIR/SWIR indices clearly outperformed the VNIR VIs. Geipel et al. (2016) also used SLR for above-ground biomass estimation with a prototype VNIR multispectral

camera system and found similar accuracies for the NDVI and REIP as estimators (R^2 of 0.7–0.84) for different growth stages in winter wheat.

Finally, only a few published studies highlight the potential of using the SWIR wavelength domain, additionally to the VNIR one. Jacques et al. (2014) document the best potential of MODIS SWIR bands for monitoring dry vegetation masses. Ramoelo et al. (2013) even conclude a very high potential of SWIR imaging data for detecting nitrogen and phosphorus in savannah grasses using airborne HyMap data. Similar findings have been reported by Mutanga and Skidmore (2004) and Mutanga et al. (2005). This study clearly shows the suitable potential of NIR/SWIR bands for forage mass monitoring. However, VNIR VIs also perform similarly or better using ASD data. Further studies have to be conducted to investigate whether UAV-based NIR/SWIR data can be used to develop more robust and better-performing estimators of forage mass monitoring.

Table 5 Statistics for SLR models of the two NIR/SWIR VIs GnyLi and NRI (WPM and ELM) and the DM yield for all 156 plots of the 39 replicates ($n=156$, $p < 0.001$)

VI	Equations	R^2	RMSE
GnyLi (ELM)	$y = 8.96x - 0.003$	0.71	0.19
GnyLi (WPM)	$y = 11.84x - 0.244$	0.73	0.18
NRI (ELM)	$y = 8.79x + 0.527$	0.73	0.18
NRI (WPM)	$y = 11.09x + 0.692$	0.75	0.17

5 Conclusion

In this study, a newly developed VNIR/SWIR multi-camera prototype was tested for its suitability for vegetation monitoring in grassland, especially for forage mass monitoring. To the authors' knowledge, this was the first flight campaign of a UAV-based VNIR/SWIR capable multi-camera 2D imaging system. The promising results, which are derived from a single flight campaign, indicate the potential of the newly developed VNIR/SWIR camera system to monitor vegetation and especially forage mass. The biomass estimation via both VIs, GnyLi and NRI, correspond well with the results of UAV- and RPM-derived sward height as forage mass estimators in the studies from Lussem et al. (2019) and Lussem et al. (2020). Lussem et al. (2019) found R^2 in the range of 0.56–0.75 for UAV-derived sward height and R^2 in the range of 0.61–0.88 for RPM derived compressed sward height. For Lussem et al. (2020) R^2 resulted from 0.54 to 0.88 for UAV-derived sward height and from 0.52 to 0.89 for RPM measurements.

Concluding from relating studies, the next research aims towards the application of the newly developed VNIR/ SWIR imaging system for UAVs in multi-temporal campaigns for monitoring grass sward development during several growth periods in a year throughout multiple years. This will also lead to a continuous improvement of the camera system and calibration routines. Furthermore, the potential for detecting nitrogen concentration, more precisely crude protein content should be further investigated. For the latter, the results reported in the literature should be investigated using full range spectral data (350–2500 nm) from field measurements using field spectroradiometers. From this data analysis, characteristic spectral bands can be identified and appropriate spectral filters applied to this novel VNIR/SWIR multi-camera system for more efficient, area-wide vegetation monitoring by UAVs.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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