

Applying UAV-based crop height to monitor biomass, N-concentration, and N-uptake in winter wheat

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Abstract

Spatial knowledge for supporting precise N fertilization is of key interest in crop management. Therefore, accurate and reliable data on crop dry biomass (DB) and N concentration (Nconc), and N-uptake (Nup) are needed considering spatial heterogeneity. While N uptake in field experiments is computed using in-situ data of DB and Nconc, it also can be directly estimated with remote sensing methods. Usually, these crop traits are derived by using optical remote or proximal sensing approaches. In this contribution, we investigate a paradigm change in providing non-destructive DB, Nconc, and Nup estimates by using non-optical data analyses but structural information extraction. Numerous studies proofed UAV-derived crop height can serve as a robust estimator for biomass. Due to the well-known negative correlation between biomass and N concentration over the growing season crop height might be used as an estimator for Nconc as well. Based on these correlations we investigate three key hypotheses: (i) crop height from UAV images using a Structure from Motion and Multiview Stereopsis (SfM/MVS) workflow serves as a very robust estimator for DB, (ii) Nconc is correlated over the growing season to DB, and (iii) DB is the dominating parameter in determining Nup. Hence, the main research question of this contribution is if UAV-derived crop height (UAV-CH) serves as a robust estimator for DB, it also can be used to directly estimate Nconc and Nup, UAV-CH in ultra-high spatial resolution (< 3 cm) is a mixed signal of crop height and density for a given spatial unit, eg. a square meter or a research plot, and therefore provides valuable crop canopy information. We present results from a 3-years effort in UAV- and in-situ data acquisition and analyses which partly support the proposed paradigm change. For each of the three years 2020, 2021, and 2022, DB can be robustly estimated using UAV-CH, having a R^2 of 0.89, 0.91, and 0.92, respectively. For Nconc and Nup the results are not as promising on a yearly analysis having R^2 for Nconc of 0.57, 0.21, and 0.41, and for Nup of 0.72, 0.61, and 0.48, respectively, but are comparable to optical approaches. However, for fertilizer recommendation, the performance on growing stage specific level is of more importance. Surprisingly, the proposed approach seems to provide similar or better results compared to optical sensing analysis showing R^2 for campaign specific days (approx. every 14 days over 3 growing periods) for N uptake between 0.57 and 0.82, and for Nconc between 0.24 and 0.78. We conclude that UAV-CH can be used as a very good and robust estimator for DB, as a moderate for Nconc, and as a moderate but robust estimator for Nup having the advantage of being more flexible in terms of less effected by weather conditions. Finally, the SfM/MVS workflow to derive UAV-CH has the potential to be fully or semifully automated from data acquisition to fertilizer recommendation.

1. Introduction

The non-destructive estimation of crop traits like dry biomass (DB) and N concentration (Nconc) are needed to compute N uptake (Nup) during the growing season. The latter is of importance in the context of precision agriculture (Mulla et al., 2013) for e.g. precision N management which optimizes N fertilization in context of crop demand and development. Spectral approaches, like the Yara N Sensor, to enable such a precise N management were introduced decades ago (Reusch, 2003). However, such spectrometer-based data acquisition does not provide spatially continuous coverage on field-level. Therefore, data acquisition approaches using Unmanned aerial Vehicles (UAVs) emerged and fill this desired information gap

(Zhang and Kovacs, 2012). UAV-based spectral sensing approaches also have limitations due to cloud cover and changing illumination. Hence, photogrammetric and laserscanning data analysis workflows were introduced to provide structural canopy data like crop height (Bendig et al., 2013; Tilly et al., 2014). Numerous studies proofed UAV-derived crop height can serve as a robust estimator for biomass (Bareth, 2021; Näsi et al. 2018). Due to the well-known negative correlation between biomass and N concentration over the growing season, Tilly and Bareth (2019) investigated crop height from terrestrial laserscanning as an estimator for biomass and Nconc for barely. In Fig. 1, the results clearly indicate the potential of using CH as a proxy for Nconc.

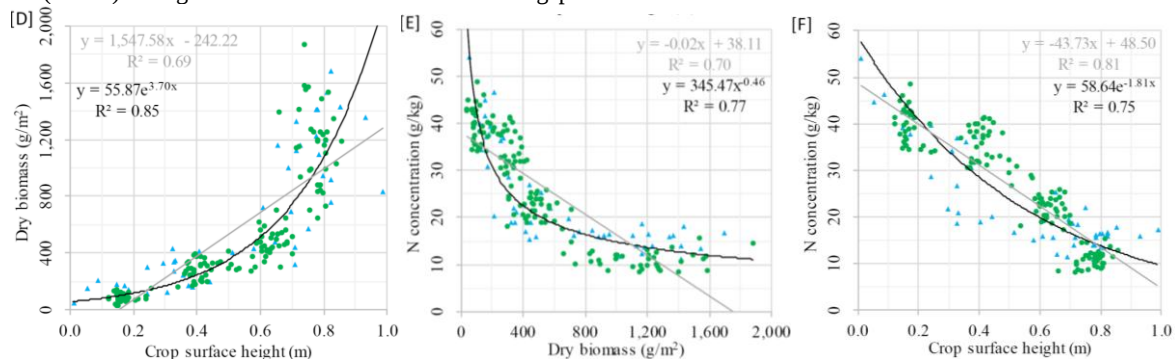


Figure 1. “Blue triangles and green dots represent the values of 2013 and 2014, respectively, with linear (light grey) and the best-fitting (black) regression lines. [D]–[F]: Crop traits plotted against each other” (Unchanged plots from Tilly et al., 2019).

Based on the results shown in Fig.1, we investigate in this contribution a paradigm change in providing non-destructive estimations of DB, Nconc, and Nup by using non-optical data analyses but structural information extraction from UAV-based RGB imagery. The three key hypotheses are that (i) crop height from UAV images using a Structure from Motion and Multiview Stereopsis (SfM/MVS) workflow serves as a very robust estimator for DB, (ii) Nconc is negatively correlated over the growing season to DB, and (iii) CH is a robust estimator for both, DB and Nconc, and can directly be used to estimate Nup. To investigate the (iii) hypothesis which represents the main objective of this study, we collected a multi annual dataset of winter wheat over three years.

2. Study Area and Methods

Study Area

In Fig.2 the winter wheat field experiment is shown. It is located at the Campus Klein-Altendorf, which is an experiment farm of the University of Bonn, located in Western Germany.

The investigated field experiment is carried out by the Institute of Crop Sciences (INRES) since 2020. The field experiment has a split-plot design with five replicates having three N-fertilizer treatments (0, 120, and 240 kg/ha) and six different wheat varieties. Plot size of the experiment plots is 7.0×1.5 m. Winter wheat is sown with a row distance of 11.3 cm. While the experiment layout is the same in all years, the location of the experiment is changing from year to year on the Campus Klein-Altendorf. In total, 18 plots per replicate and 90 plots for the whole experiment are managed. Two of the five replicates are selected for destructive sampling. In Fig.2, row 2 and 4 are highlighted to indicate these replicates. In contrast to the growing season 2020 with only one row used for destructive sampling ($n = 18$), 36 plots were sampled for each UAV campaign in 2021 and 2022. An area of 1 m by 0.3 m was destructively sampled for each of the 36 plots directly after each UAV campaign and laboratory analysis provide dry biomass (DB) and nitrogen concentration (Nconc). From the latter two nitrogen uptake (Nup) is calculated.

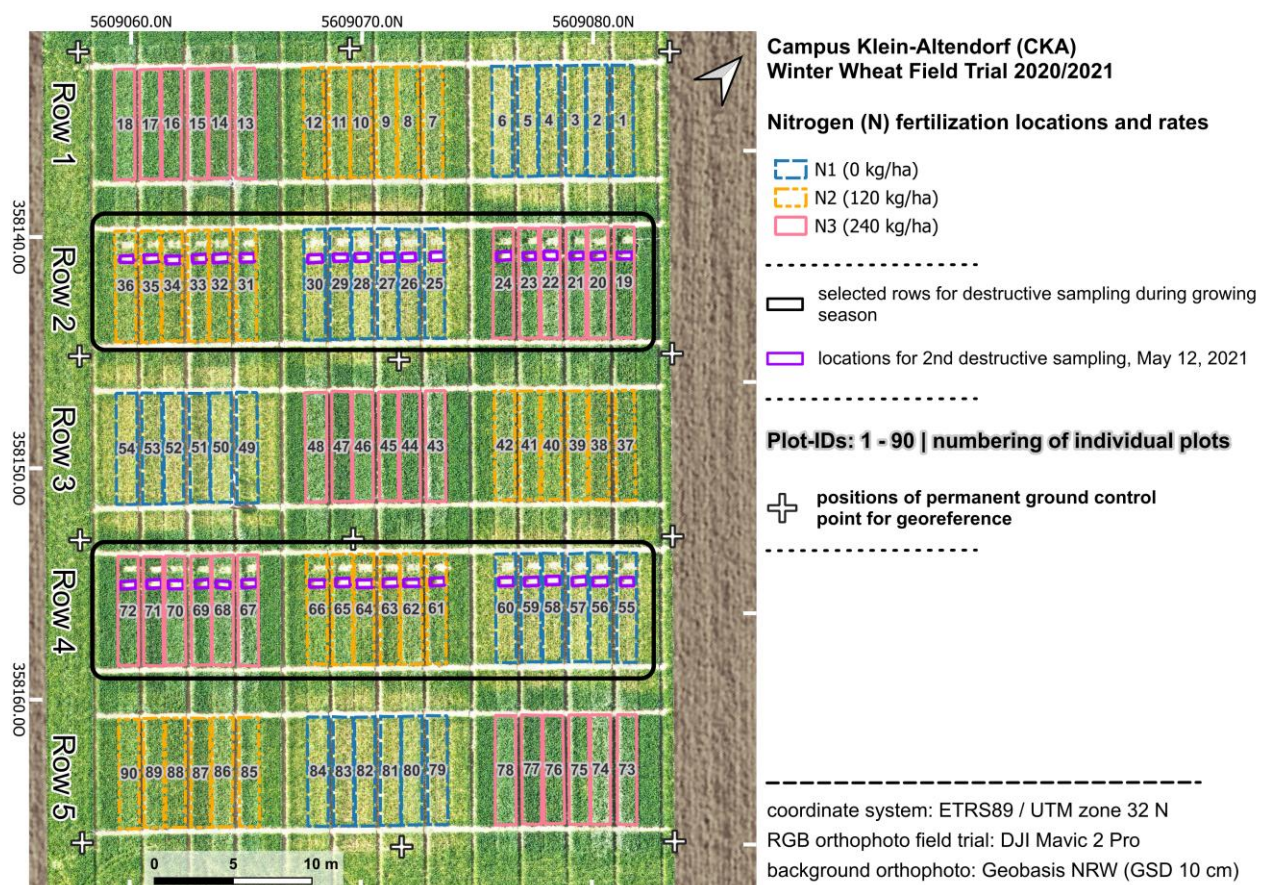


Figure 2. Layout of the winter wheat experiment since 2020 at the Campus Klein-Altendorf (CKA). A Digital Orthophoto (DOP) of 12 May 2021, plot outlines and areas of destructive samplings in row 2 and 4 (black outlines) are shown. (Figure unchanged from Jenal et al., 2025)

UAV-Based Image Acquisition and Analysis

A DJI Phantom 4 RTK (P4RTK) was flown in 2020, 2021, and 2022 for a total of 17 campaigns during the three growing seasons: 26.03., 08.04., 28.04., 13.05., 26.05., and 12.06.2020; 25.02., 20.04., 12.05., 28.05., and 11.06.2021; 04.03., 12.04., 28.04., 11.05., 25.05., 14.06.2022. The P4RTK is equipped with a fully gimbaled 1" 20 MP RGB sensor. Around 460 images were collected during each campaign with a Ground Sampling Distance (GSD) of 0.0067 m. Along- and across-track image

overlapping was $> 80\%$ flying an orthogonal pattern which resulted in a total image overlap of $> 90\%$. Flying altitude above ground was between 25 and 28 m.

The image data was processed in a SfM/MVS analysis workflow (Turner et al., 2012) using Agisoft Metashape. The detailed analysis specifications for 2020 are described in Jenal et al. (2021) while the analysis workflow for 2021 and 2022 followed the proposed method of Bareth et al. (2023). The major difference in the two workflows is that Jenal et al. (2020)

used ground control points (GCPs) while for 2021 and 2022 no GCPs were used but direct RTK georeferencing as suggested by Bareth and Hütt (2023). The GSD of the processed Digital Orthophoto (DOP) is 0.0067 m and of the Digital Surface Model (DSM) is 0.0137 m. For crop height analysis, the DSMs were analysed according to the described crop height extraction method by Bendig et al. (2013).



Figure 3. DJI P4 RTK.

3. Results

For each year, bivariate regression analysis was performed for each investigated trait (DB, Nconc, and Nup) against CH with 18 destructive samplings in 2020 and 36 destructive samplings in 2021 and 2022. Because the field experiment is not located in the same place each year but at different sites with different land use before and varying soil conditions, the data sets are considered independent. In Fig 3, the results for 2021 and 2022 are visualized. The very good performance of CH to estimate DB with a R^2 of 0.89 in 2020 (Jenal et al. 2020) is reproduced with R^2 of 0.91 and 0.92 in 2021 and 2022, respectively. The very promising performance of CH for Nconc ($R^2 = 0.57$) and Nup ($R^2 = 0.72$) could not be found in 2021 and 2022. In both years R^2 for Nconc (2021: 0.21; 2022: 0.41) and Nup (2021: 0.61; 2022: 0.48) were significantly lower compared to 2020 (Bareth et al. 2025). Summarizing the data of all three years yielded R^2 of 0.89 for DB, 0.35 for Nconc, and 0.57 for Nup.

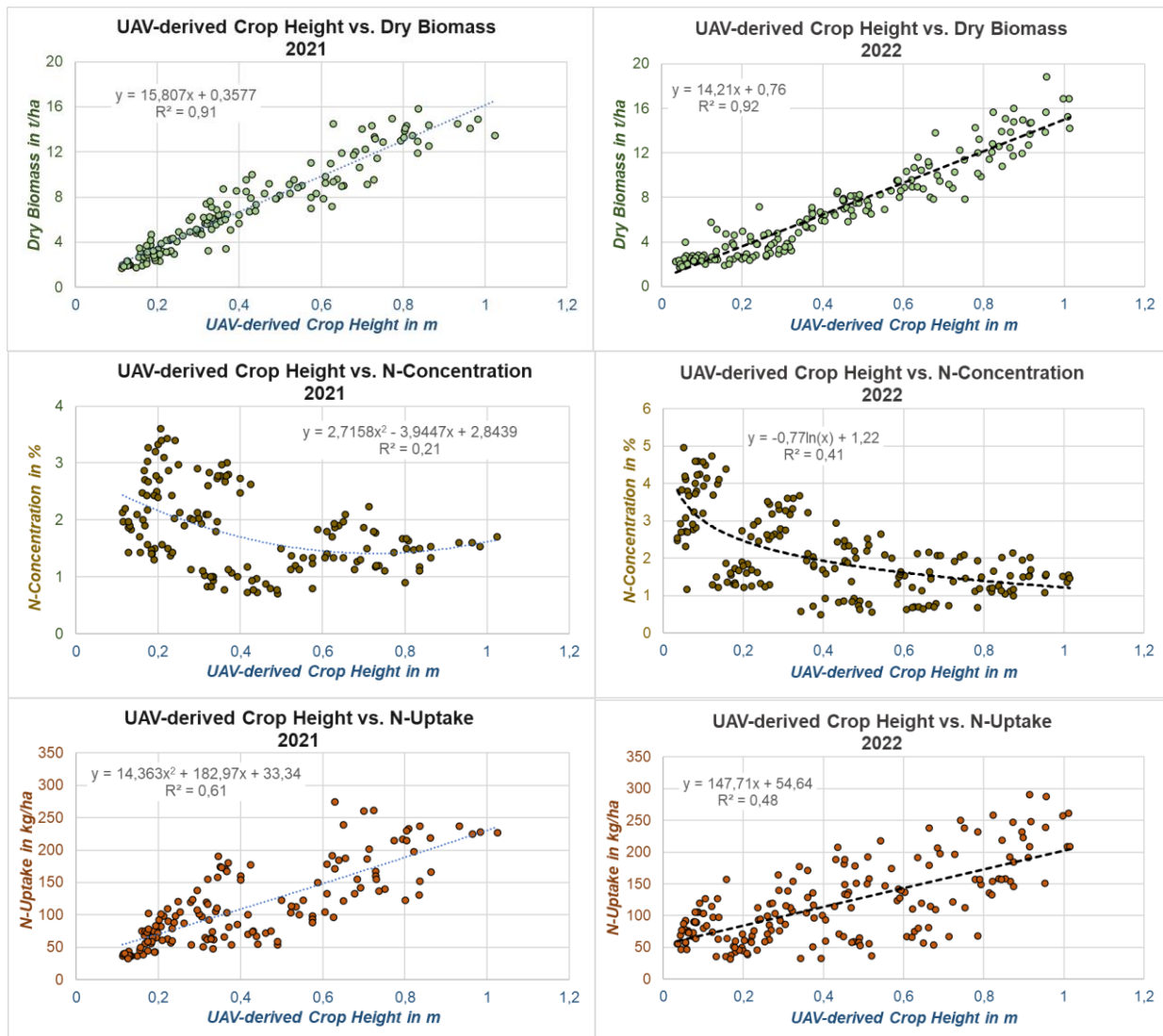


Figure 4. UAV-derived crop height (CH) plotted vs. the investigated traits DB, Nconc, and Nup using annual data for 2021 and 2022.

While the performance on annual data sets is not overall convincing, the analysis on date specific data is surprisingly better and for practical crop management more important (Bareth et al. 2025). Estimators have to work on a growing stage specific temporal scale. Campaign specific data analysis resulted in R^2 for DB between 0.22 and 0.83, for Nconc

between 0.24 and 0.78, and for Nupe between 0.57 and 0.84. In Fig.4, single date analysis for 12.05.2021 (Bareth et al. 2025) and 11.05.2022 are shown. For both years, CH serves as a good to very good estimator with moderate to high R^2 for DB (2021: 0.83; 2022: 0.68), Nconc (2021:0.73; 2022:0.70), and for Nup (2021: 0.84; 2022: 0.75).

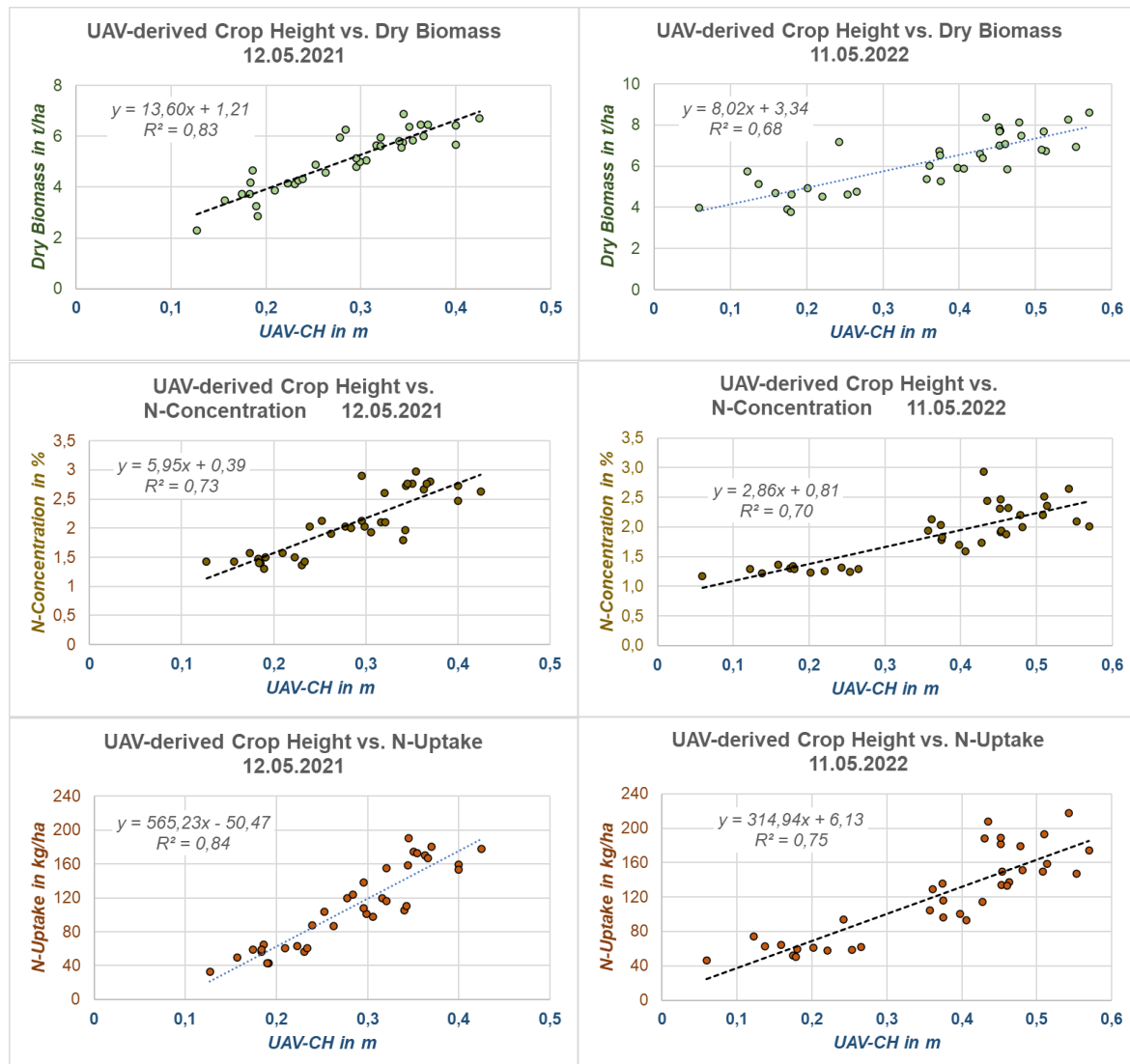


Figure 5. Campaign specific analysis for two selected campaigns, 12 May 2021 and 11 May 2022. For both dates, CH is plotted vs. DB, Nconc, and Nup.

Pooling the three years data for annual time windows of 5-10 days representing a first analysis of four growing stage-like specific analysis yielded moderate to good R^2 . The results are listed in Tab.1.

Annual time window	DB	Nconc	Nup
Early May	0.47	0.48	0.63
Mid May	0.65	0.45	0.68
Early June	0.53	0.55	0.60
Mid June	0.69	0.47	0.61

Table 1. Grouping the date-specific campaigns into annual time windows for 2020,2021, and 2022 for growing stage-like regression analysis against UAV-derived crop height.

To investigate the potential of CH as an estimator for Nup, the regression models for the different annual time windows derived from the analysis presented in Tab.1 were applied to crop height data of an independent dataset from 2023. The field experiment as described above for the years 2020 to 2022 were also investigated in 2023. The modelled results are validated against destructive sampling and laboratory analysis of 2023. The results are visualized in Fig.6. Corresponding RMSE values are 101, 40, 56, and 53 kg/ha for the early May, mid May, early June, and mid June, respectively.

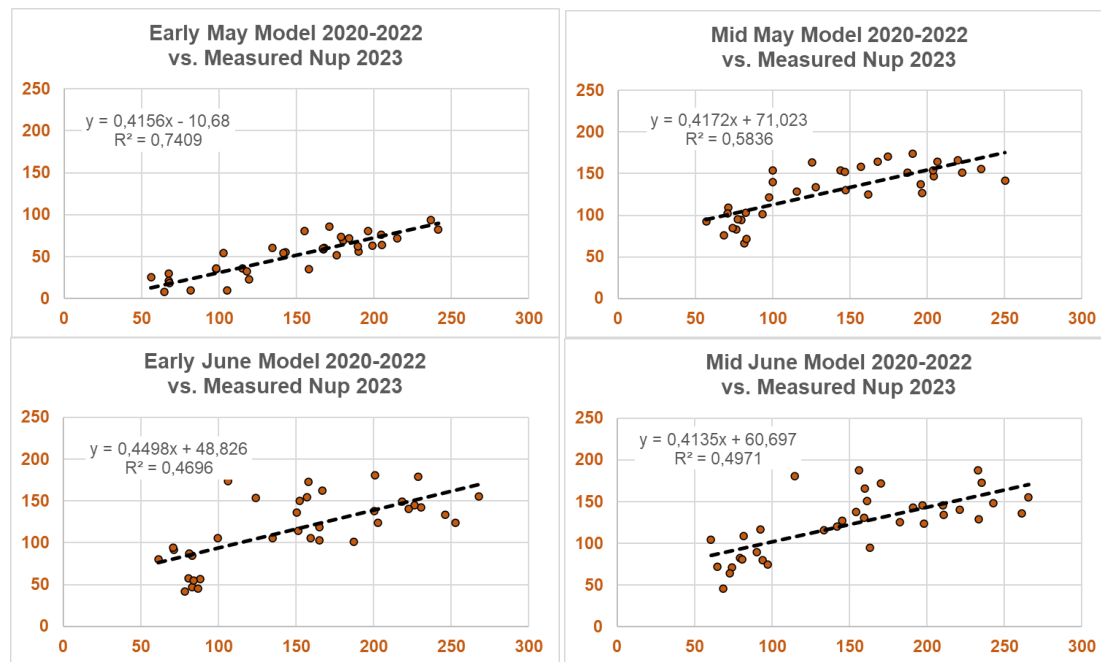


Figure 6. CH-based modelled Nup (y-axis) plotted versus measured Nup (x-axis) in kg/ha for the four investigated annual time windows for 2023. UAV-derived CH for 2023 was generated according to the analysis workflow without using GCPs applied for 2021 to 2022.

4. Discussion

Bendig et al. (2013 and 2014) introduced UAV-derived crop height (CH) as an estimator for dry biomass (DB) in barley. Similar findings are published using terrestrial laserscanning to derive CH as an DB-estimator by Tilly et al. (2014). Tilly and Bareth (2019) further investigated CH as an estimator for N concentration (Nconc) using biomass regression models and documented very promising results. Similar findings are reported by Näsi et al. (2018) and Jenal et al. (2025). In this contribution, we investigated UAV-derived CH serving as a direct predictor for N uptake (Nup) due to the correlation to DB and Nconc. Precondition is the ability of CH to be a robust estimator for DB and Nconc, both are used to compute Nup. The performance of CH to estimate the three investigated traits varies significantly over the years. However, CH serves as a good and robust estimator for DB on annual data and for growing stage specific analysis. For Nconc the performance is moderate and seems not robust for both, annual and growing stage specific analysis. Finally, for Nup the results are promising reporting moderate and robust R^2 for annual and growing stage specific analysis (0.47 to 0.74). Argento et al. reported similar correlation for optical satellite and UAV-based optical approaches ($r > 0.8$). Hütt et al. (2023) reported similar findings for UAV-based laserscanning and CH metrics. Li et al. (2008) and Li et al. (2010) investigated spectral vegetation indices (VIs) of the visible and near-infrared (VIS/NIR) domain for Nconc in winter wheat for growing stage specific analysis. The modelling performance of established VIs like NDVI, REIP, OSAVI, MCARI etc. were not given and only yielded R^2 0.08 to 0.33 for an independent data set. Moderate results were achieved by pooling the data on an annual base. R^2 are ranging between 0.54 and 0.58 in 2006 and between 0.39 and 0.44 for 2007 (Li et al. 2010). All three traits (DB, Nconc, and Nup) were analysed by Li et al. (2008) as a pooled dataset comprising 2006 and 2007 and resulted in R^2 between 0.7 and 0.78 for DB, between 0.36 and 0.43 for Nconc, and between 0.74 and 0.84 for Nup. Similar results were

reported by Näsi for spectral and CH analysis approaches. Pooling the data of this study for 2021 and 2022 for CH-analysis result in following R^2 : 0.91, 0.92 for DB, 0.21 and 0.42 for Nconc, and 0.61 and 0.48 for Nup. Additionally, Jenal et al. (2025) investigated differently acquired SfM/SVM CH data for 12 May 2021. Similar performance as presented in our study using the P4RTK data are reported. Comparing our results to published findings using spectral data analysis approaches, Nconc and Nup can be better estimated using spectral sensing methods while CH-based modelling of DB can compete or perform even better. However, to produce good and robust results with spectral sensing methods, clear sky weather conditions are required and data acquisition has to take place around solar noon. Both limit the applicability severely in management applications.

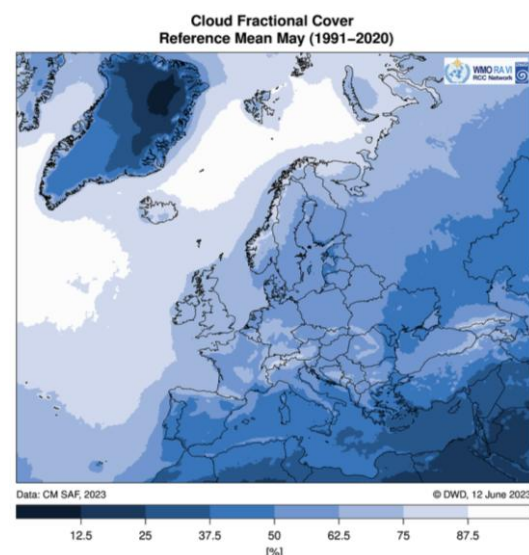


Figure 7. Average May cloud cover in Europe (www.dwd.de).

In Fig.7, average cloud cover is shown for Europe for May. It is clearly visible that for most middle European countries severe limitations for spectral sensing occur due to cloud cover values between 62.5 and 87.5 % in average. In contrast, UAV-derived CH can be derived under varying weather condition and enables more flexible data acquisition. The latter is important for the development for farming applications. Finally, The data analysis workflow presented in this study not using GCPs but direct RTK-based georeferencing could enable automatized, cloud-based data analysis and provision of N fertilization recommendation maps within hours of image acquisition.

5. Conclusions

In our study we could show that UAV-derived crop height (CH) is a robust estimator for dry biomass (DB) for winter wheat for growing stage-like analysis. It clearly performs in linear regression models as good as spectral approaches or even better. For N concentration (Nconc) the performance is significantly weaker and not comparable to spectral VIS/NIR approaches. However, the correlation can only be as good as the correlation between dry biomass and Nconc. Finally, CH performs as a predictor for N uptake (Nup) weaker in comparison to dry biomass but seems to be a moderate and robust estimator. In general, a very good estimator for DB serves as a good to moderate estimator for Nup. Further investigation will be carried out focusing on Nup model development using CH and validation. Besides, we already have collected a six years data set of this winter wheat field experiment which will enable intensive validations. Due to challenging weather conditions during the growing season in many European countries, CH can be used to fill data gaps of spectral approaches or for the combination of spectral and structural analysis.

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