Deriving Sward Height from UAVs

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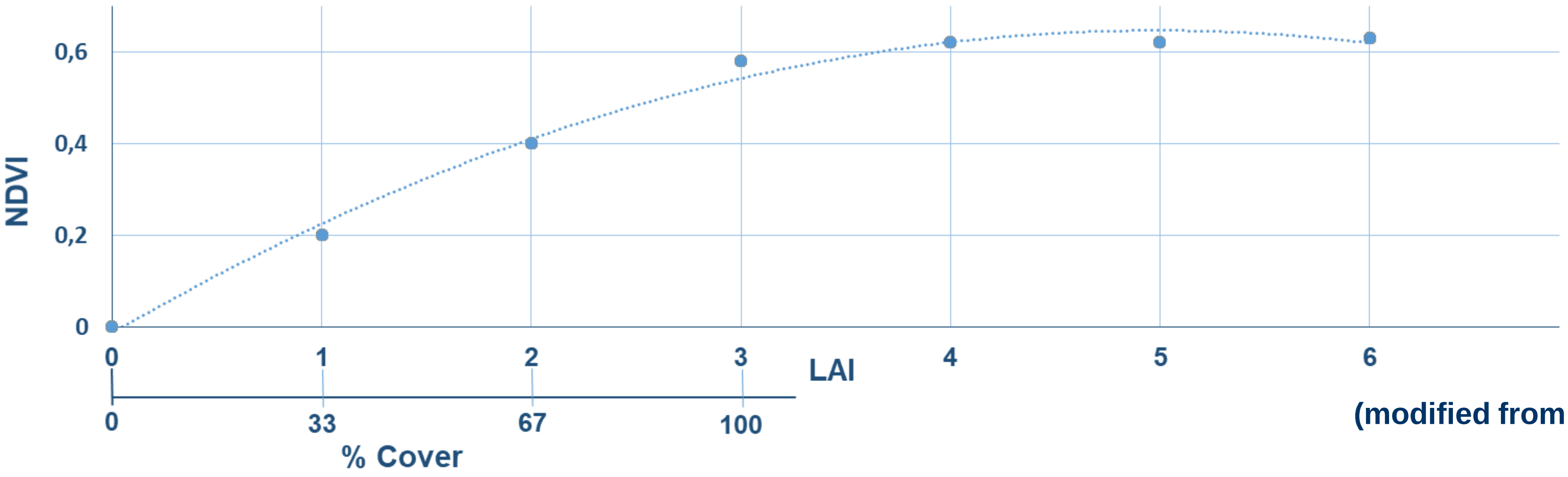
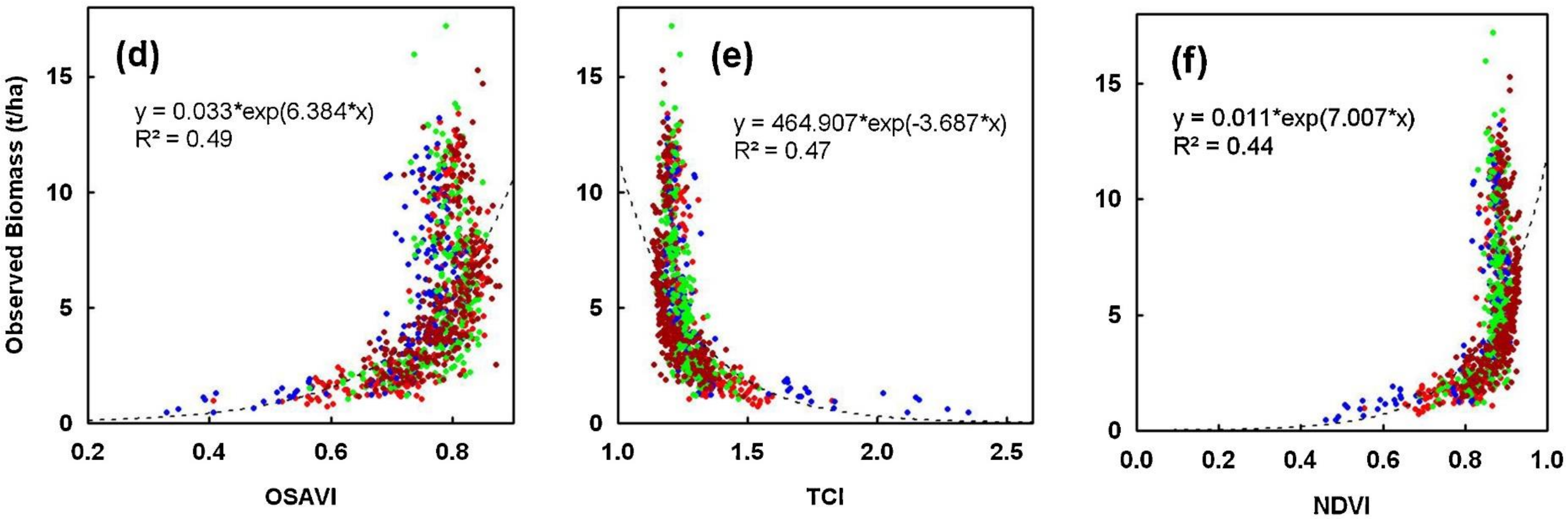
Saturation of VIs



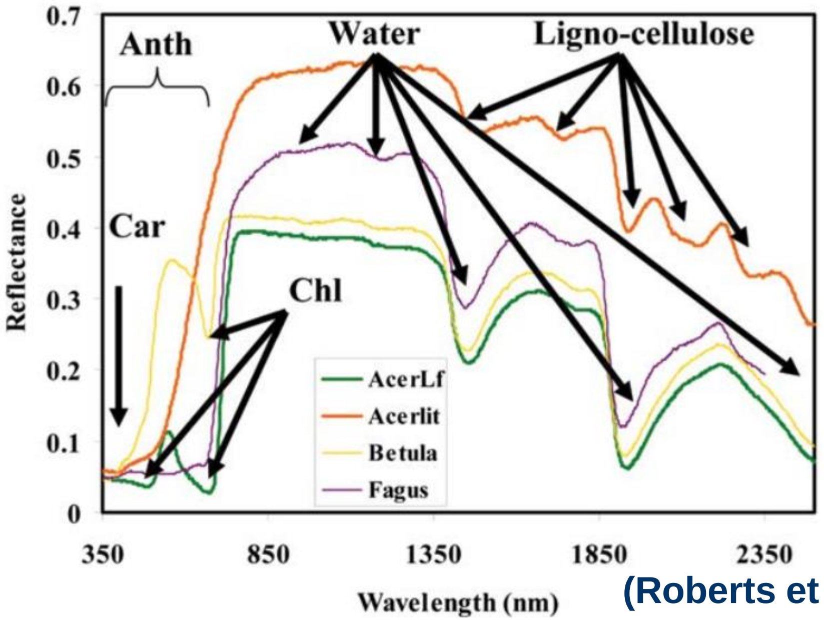
(modified from Carlson et al. 1990)



(Gnyp et al. 2014)

Motivation & Definitions: Nonspectral Crop Traits (field level)

Spectral Crop Traits



(Roberts et al. 2019)

- spectral properties
- fraction of absorbed photosynthetically active radiation (fAPAR)
- chlorophyll, carotinoides, lignin …
- vegetation indices
- …

spectral predictors

Nonspectral Crop Traits

- crop height / volume
- sowing density
- fractional vegetation cover
- leave area index
- biomass
- nitrogen concentration / uptake
- …

in situ

(Marshall &Thenkabail 2015; Aasen & Bareth 2019)

Non-spectral pre-dictors

3D data:

- photogrammetry
- laser scanning
- ultra sonic
- …

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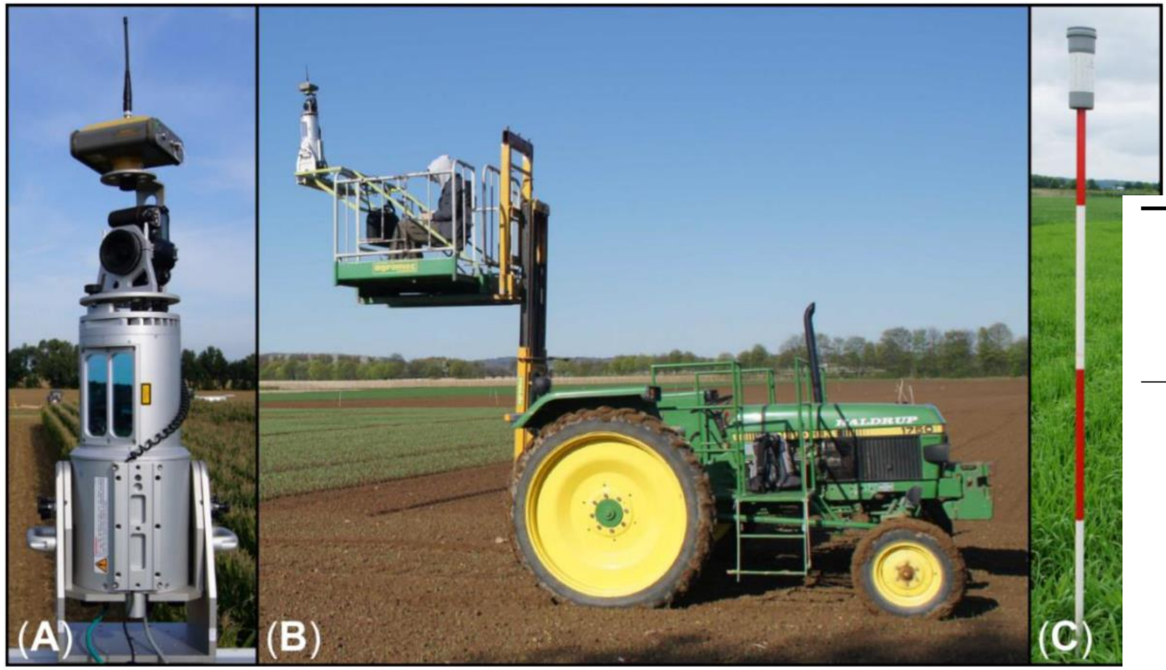
Status Quo 3D: Tilly et al. 2015 & Bendig et al. 2015



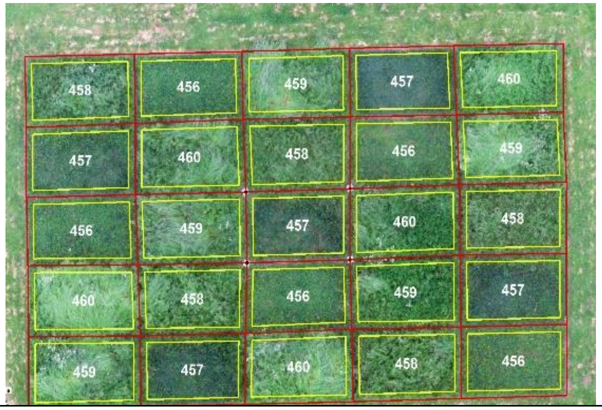
			Bivariate BRMs					Multivariate BRMs			
			Whole Period		Pre-Anthesis			Whole Period		Pre-Anthesis	
		Estimator	R^2	SE_E[a]	R^2	SE_E[a]	Estimator[b]	R^2	SE_E[a]	R^2	SE_E[a]
Dry biomass	Linear	*PH*	*0.65*	*250.71*	*0.76*	*143.34*					
		GnyLi	0.52	293.80	0.68	166.75	GnyLi	0.65	865.76	0.77	635.30
		NDVI	0.07	409.44	0.34	239.09	NDVI	0.69	537.36	0.76	518.25
		NRI	0.54	289.57	0.70	159.97	NRI	0.65	876.08	0.77	621.60
		RDVI	0.13	396.88	0.39	230.33	RDVI	0.69	479.48	0.76	535.08
		REIP	0.12	398.08	0.58	189.95	REIP	0.73	48353.45	0.76	6462.41
		RGBVI	0.05	413.80	0.26	252.59	RGBVI	0.68	557.08	0.76	580.76
	Exponential	*PH*	*0.84*	*0.37*	*0.84*	*0.34*					
		GnyLi	0.80	0.42	0.85	0.32	GnyLi	0.86	2.43	0.88	2.14
		NDVI	0.30	0.77	0.61	0.53	NDVI	0.85	2.85	0.88	3.99
		NRI	0.81	0.40	0.87	0.30	NRI	0.87	2.29	0.89	1.96
		RDVI	0.41	0.71	0.68	0.48	RDVI	0.85	2.52	0.88	2.84
		REIP	0.37	0.73	0.77	0.40	REIP	0.84	30.39	0.86	48.43
		RGBVI	0.23	0.81	0.48	0.60	RGBVI	0.85	2.51	0.87	2.73

Tilly et al. (2015): Fusion of Plant Height and Vegetation Indices for the Estimation of Barley Biomass. Remote Sensing 7, pp.11449-11480. DOI:10.3390/rs70911449

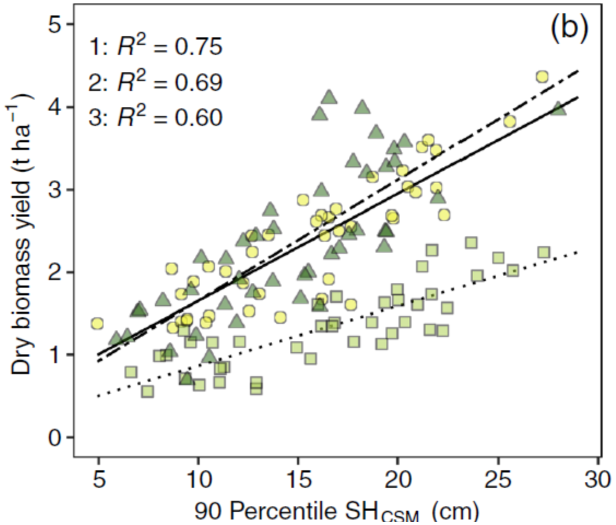
Bendig et al. (2015): Combining UAV-based Crop Surface Models, Visible and Near Infrared Vegetation Indices for Biomass Monitoring in Barley. Int. J. Appl. Earth Obs. Geoinf. 39, 79-87. doi:10.1016/j.jag.2015.02.012

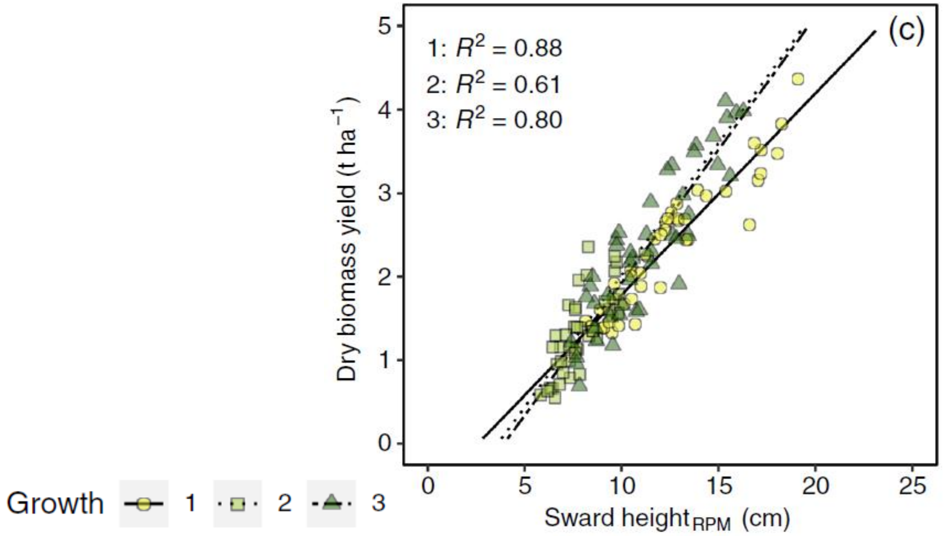
Status Quo:

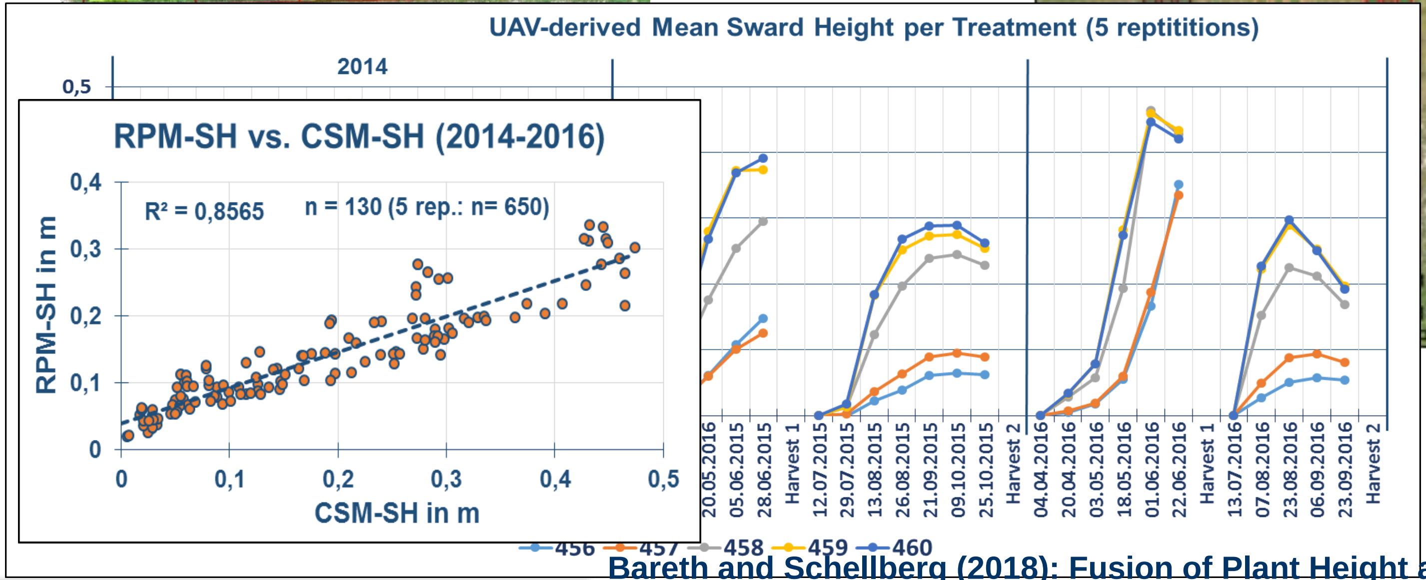
Rengen (2014-2017)



Klein-Altendorf (2014-2017)





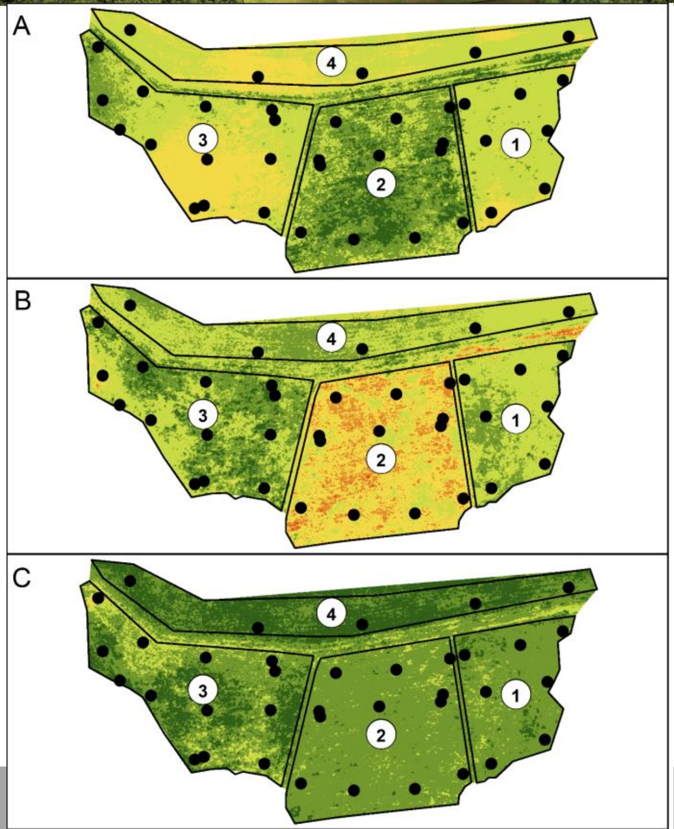


Lussem et al.: (2019, in print): Estimating biomass in temperate grassland with high resolution canopy surface models from unmanned aerial vehicle-based RGB images and vegetation indices. JARS.

Bareth and Schellberg (2018): Fusion of Plant Height and Vegetation Indices for the Estimation of Barley Biomass. Remote Sensing 7, pp.11449-11480. DOI:10.3390/rs70911449

Case studies: Pastures

Horse-grazed Grassland: 1.6 ha (Hoffmeister et al. 2018)



BMBF-funded GreenGrass-Projekt (2019-2024): Versuchsgut Relliehausen (9 ha)

Conclusion and Discussion

- Compressed sward height performs very well as nonspectral estimator!
- UAV-derived sward height performs moderate to well!
- Potential is not fully exploited yet: histogram, 3D … !
- Direct georeferencing!
- Robustness and transferability!

Näsi et al. (2018): Estimating biomass and nitrogen amount of barley and grass using UAV and aircraft based spectral and photogrammetric 3D features. Remote Sensing 10 (7): 1082. doi: 10.3390/rs10071082

Abstract:
"… . Our objective was to develop and assess a methodology for crop biomass and nitrogen estimation, integrating spectral and 3D features that can be extracted using airborne miniaturized multispectral, hyperspectral and colour (RGB) cameras. … . In the biomass estimation, the best results were obtained when integrating hyperspectral and 3D features, but the integration of RGB images and 3D features also provided results that were almost as good. In nitrogen content estimation, the hyperspectral camera gave the best results. … ."

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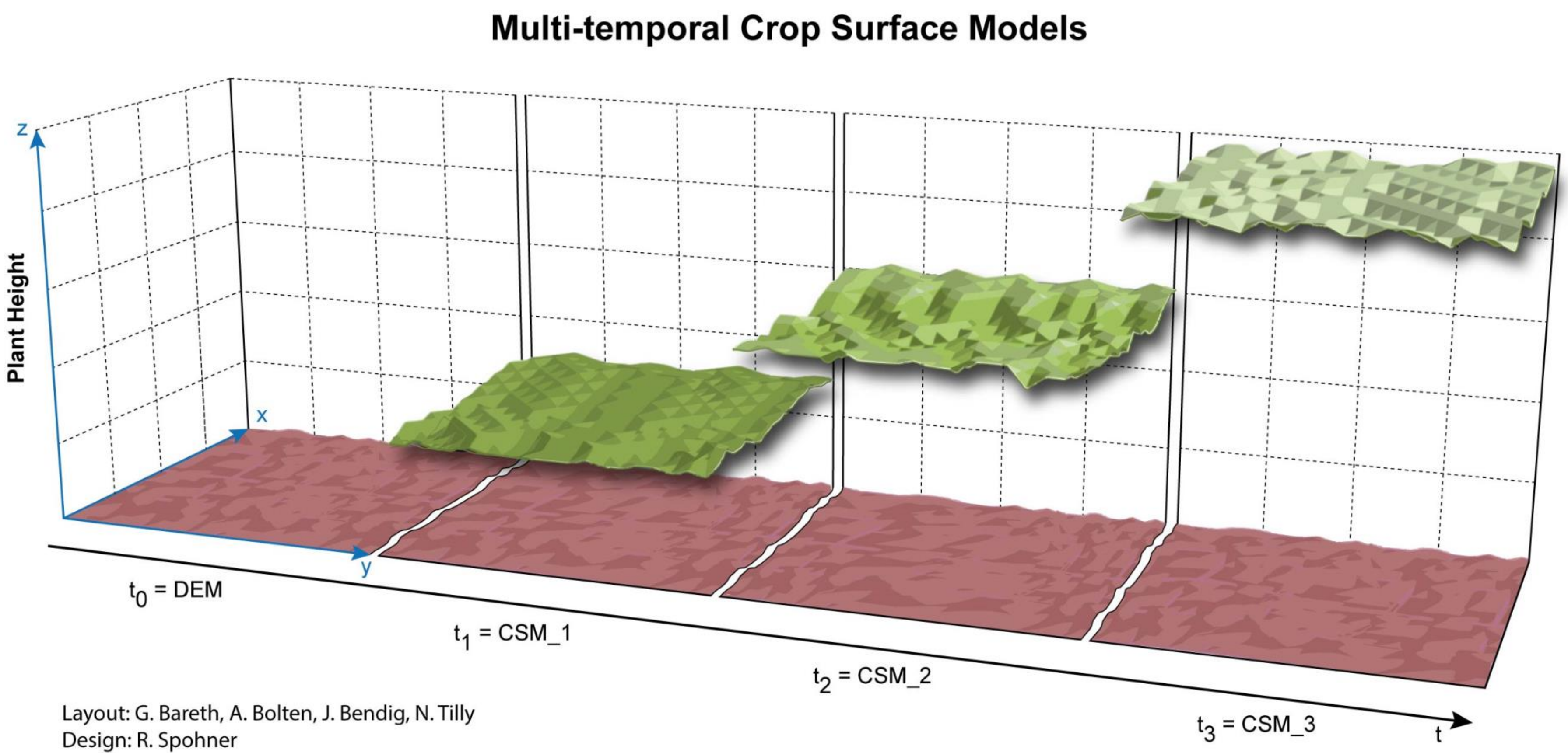
Crop Surface Model (CSM)



Plant Height$_{total}$ = $t_3 - t_0$
Plant Height$_{in\text{-}season1}$ = $t_1 - t_0$
Plant Height$_{in\text{-}season2}$ = $t_2 - t_0$

Plant Growth$_{in\text{-}season3}$ = $t_2 - t_1$
Plant Growth$_{in\text{-}season4}$ = $t_3 - t_2$
Plant Growth$_{in\text{-}season5}$ = $t_3 - t_1$

HOFFMEISTER et al. (2010): High resolution CSM and CVM on field level by terrestrial lasers canning. In: Proc SPIE, Vol. 7840, 78400E: DOI: 10.1117/12.872315

New Papers: Grassland, UAVs, Machine Learning

4. Discussion

We developed and assessed a novel drone-based machine learning technique for estimating the height, fresh yield (FY) and dry matter yield (DMY) of grass swards. Our approach was to derive various features from the multispectral photogrammetric data sets, including the height features from the CHM and the colours and different VIs from orthophotos in the red (R), green (G), blue (B) and near-infrared (NIR) spectral bands. The MLR and RF estimators were trained using high variation timothy/meadow fescues mixture swards dominated by timothy.

Our study was the first to integrate various structural and spectral features from a drone multispectral photogrammetric system using machine learning techniques for the grass sward biomass estimation in the context of silage production. The best results were obtained when combining different height, RGB and VI features. The correlations and RMSEs were at best 0.98 and 0.34 t/ha (12.7%) for the DMY and 0.98 and 1.22 t/ha (11.05%) for the FY, respectively. The MLR and RF provided quite similar results (Table 10). Overall, the most important features for the RF were the new indices ExG + H_{p90} and ExG + H_{max} (introduced in this study), the height features and the GrassI (Table 11 and Appendix B, Table A5). Additionally, the CHM-features gave better correlations to the DMY and the FY than the regressions with the physical canopy height measurements by the height stick (H_{ref}) at the three growth stages of the silage sward studied resulting from the three first measurement dates.

Table 9. Pearson correlation coefficients for VIs and DMY, FY and H_{ref} on different dates and different Nitrogen fertilizer levels (0–150 kg/ha). DMY: dry matter yield; FY: fresh yield; and H_{ref}: reference height measurement.

	Date				N-Level (kg/ha)					
	6 June	15 June	19 June	28 June	0	50	75	100	125	150
DMY										
MSAVI	0.95	0.94	0.96	0.95	0.62	0.91	0.90	0.91	0.87	0.94
NDVI	0.92	0.94	0.94	0.89	0.75	0.95	0.94	0.95	0.88	0.91
ExG	0.77	0.75	0.87	0.89	0.75	0.88	0.68	0.84	0.85	0.90
ExG + H_{p90}	0.91	0.94	0.96	0.90	0.80	0.92	0.96	0.96	0.93	0.88
$GrassI_{p90}$	0.88	0.91	0.96	0.90	0.87	0.89	0.95	0.94	0.92	0.89
FY										
MSAVI	0.96	0.95	0.97	0.99	0.59	0.95	0.87	0.90	0.94	0.92
NDVI	0.94	0.92	0.92	0.81	0.73	0.95	0.92	0.94	0.96	0.91
ExG	0.82	0.71	0.84	0.89	0.77	0.94	0.79	0.89	0.92	0.91
ExG + H_{p90}	0.95	0.92	0.94	0.83	0.75	0.98	0.99	0.98	0.98	0.91
$GrassI_{p90}$	0.93	0.88	0.92	0.85	0.87	0.98	0.99	0.98	0.98	0.94
H_{ref}										
MSAVI	0.85	0.94	0.93	0.81	0.71	0.89	0.89	0.85	0.88	0.87
NDVI	0.86	0.97	0.94	0.88	0.77	0.93	0.95	0.92	0.89	0.86
ExG	0.72	0.85	0.89	0.76	0.75	0.88	0.71	0.87	0.79	0.85
ExG + H_{p90}	0.84	0.97	0.96	0.89	0.76	0.93	0.99	0.97	0.88	0.94
$GrassI_{p90}$	0.82	0.96	0.96	0.89	0.80	0.93	0.98	0.97	0.89	0.95

agriculture

MDPI

Article

A Novel Machine Learning Method for Estimating Biomass of Grass Swards Using a Photogrammetric Canopy Height Model, Images and Vegetation Indices Captured by a Drone

Niko Viljanen [1,*], Eija Honkavaara [1], Roope Näsi [1], Teemu Hakala [1], Oiva Niemeläinen [2] and Jere Kaivosoja [2]