Above ground biomass and growth across paddocks from space for characterising soil constraints and N availability

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Abstract

Increasingly, agronomic research is moving from small plot to paddock scale trials, where spatial, non-destructive measurements of crop production are needed. Estimation of above ground biomass (AGB) and crop phenology from satellite vegetation index time series is not new, but the methods are not entirely straightforward. One of the challenges is differences in the satellite index response due to differences in sensors, soil background, spatial scales and crop response. In this paper we focus on the use of the public domain Sentinel-2 imagery to estimate AGB across paddocks based on time series of Normalized Difference Vegetation Index (NDVI) values. Using a pooled dataset across 14 paddocks (mostly wheat and barley) and three growing seasons, linear regression of AGB on cumulative NDVI resulted in an R^2 of 0.77 and a standard error of 2056 kg ha^{-1}. Establishing the relationship for a single paddock and crop generally improved the R^2 and standard error results, with R^2 values up to 0.94 and standard errors of 1092 kg ha^{-1}. While further refinements to the techniques are being developed, these results are being used to provide AGB estimates and growth rate differences for research in soil constraints and improved N application for precision agriculture.

Keywords

Remote sensing, spatial measurements, NDVI time series, crop sensors.

Introduction

Estimation of above ground biomass (AGB) and crop phenology from satellite time series dates back to the early 1980's (e.g., Tucker et al. 1981, Asrar et al. 1985), but the methods are not entirely straightforward. The methods rely on time series of vegetation indices such as the Normalised Vegetation Difference Index (NDVI) (Rouse et al. 1973). One of the challenges is differences in the index response due to differences in sensors, soil background, spatial scales and crop response. We are developing methods to overcome gaps from clouds, such as cross calibration of different imagery and ground-based sources, and to normalise relationships across different paddocks. In this paper we focus on the use of the public domain Sentinel-2 imagery (https://sentinel.esa.int/web/sentinel/home) to estimate spatial AGB and growth rates across paddocks using NDVI time series.

Methods

Datasets used

To evaluate the robustness of the techniques, we have pooled data from 14 paddocks in South Australia and Victoria, across three growing seasons (2018-2020), multiple growth stages, and four different crops (although primarily wheat and barley). The dataset we evaluated consists of paired measurements of AGB and cumulative NDVI from time series.

Determining AGB

Standard methods using dried and weighed sample biomass cuts (e.g., 4 rows by 1 m length) were used to estimate AGB. Biomass cuts were taken for each paddock at least once during the season, and up to 8 times, with samples taken at 9-60 sites.

Cumulative NDVI from satellite time series

Atmospherically corrected Sentinel-2 satellite imagery was used to generate NDVI time series for each 10 m pixel within each paddock. These time series were smoothed and interpolated using the LOESS function in a series of steps as detailed in Fig. 1a. At each pixel, the small integral was calculated at daily time steps (Fig. 1b). The final dataset is a stack of images of cumulative NDVI through time.

Software used

ENVI/IDL software (Harris Geospatial Solutions, Inc., Boulder, CO, USA) was used for image processing. R was used for image processing and regression analysis (R Core Team 2020), and QGIS (QGIS 2021) for spatial data management and analysis.

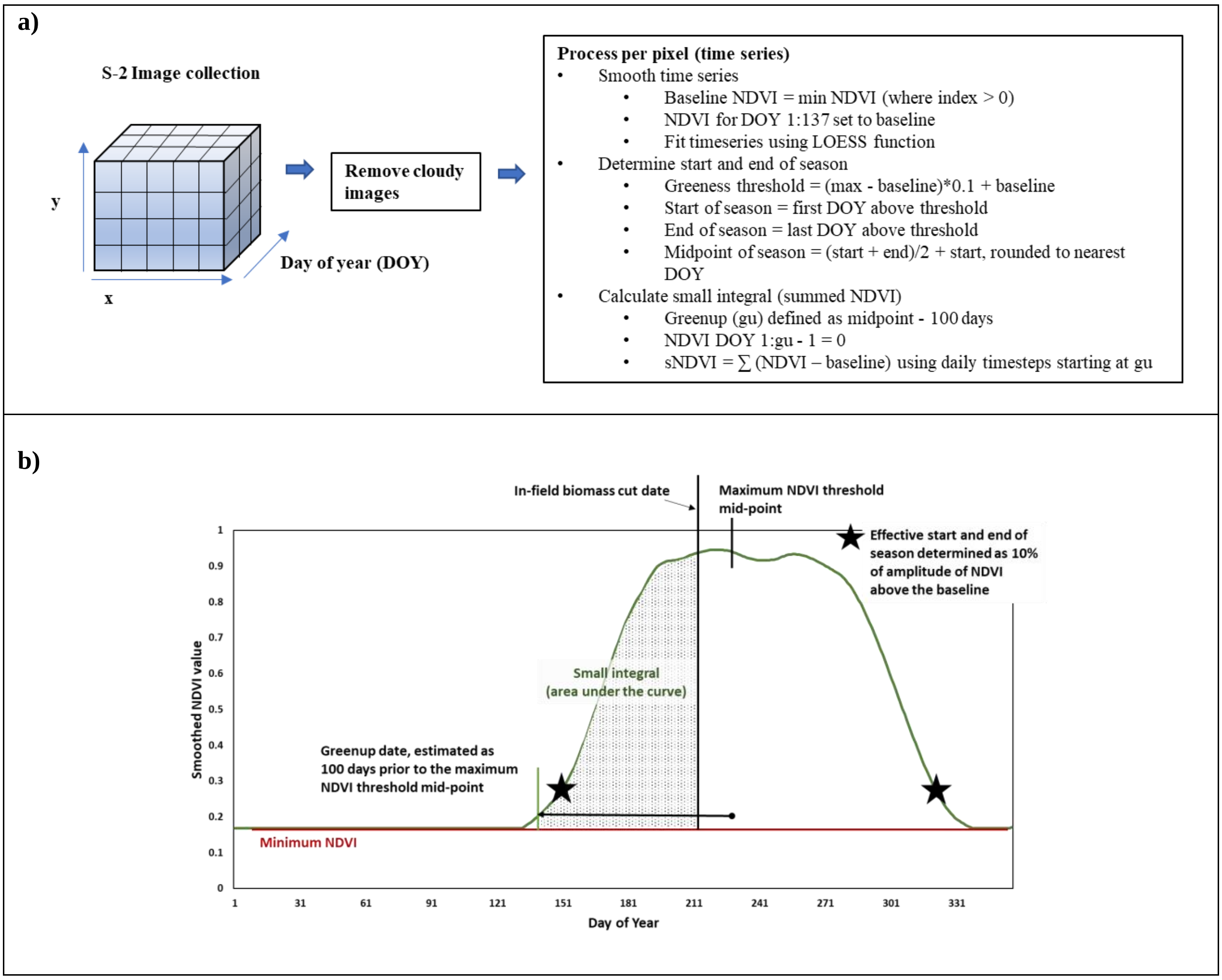

Figure 1. Summed (cumulative) NDVI was determined for each biomass cut date using per pixel-level timeseries as described in (a). An example time series and the corresponding integral is shown in (b).

Results

The relationship between AGB and cumulative NDVI for the entire dataset is shown in Fig. 2, and the corresponding regression results are presented in Table 1. The pooled data resulted in an R^2 of 0.77 and standard error of 2056 kg ha^{-1}. Regressions were also performed on seven individual paddocks (included in the pooled dataset) where data at multiple growth stages were available. The regression results for these individual paddocks (Table 2) yielded R^2 values from 0.71 to 0.94, although the R^2 values for five of the seven paddocks were higher than the results of the pooled analysis. Standard errors ranged from 1043 to 2002 kg ha^{-1}, but as with the R^2, five of the seven paddocks had lower standard errors than the pooled data.

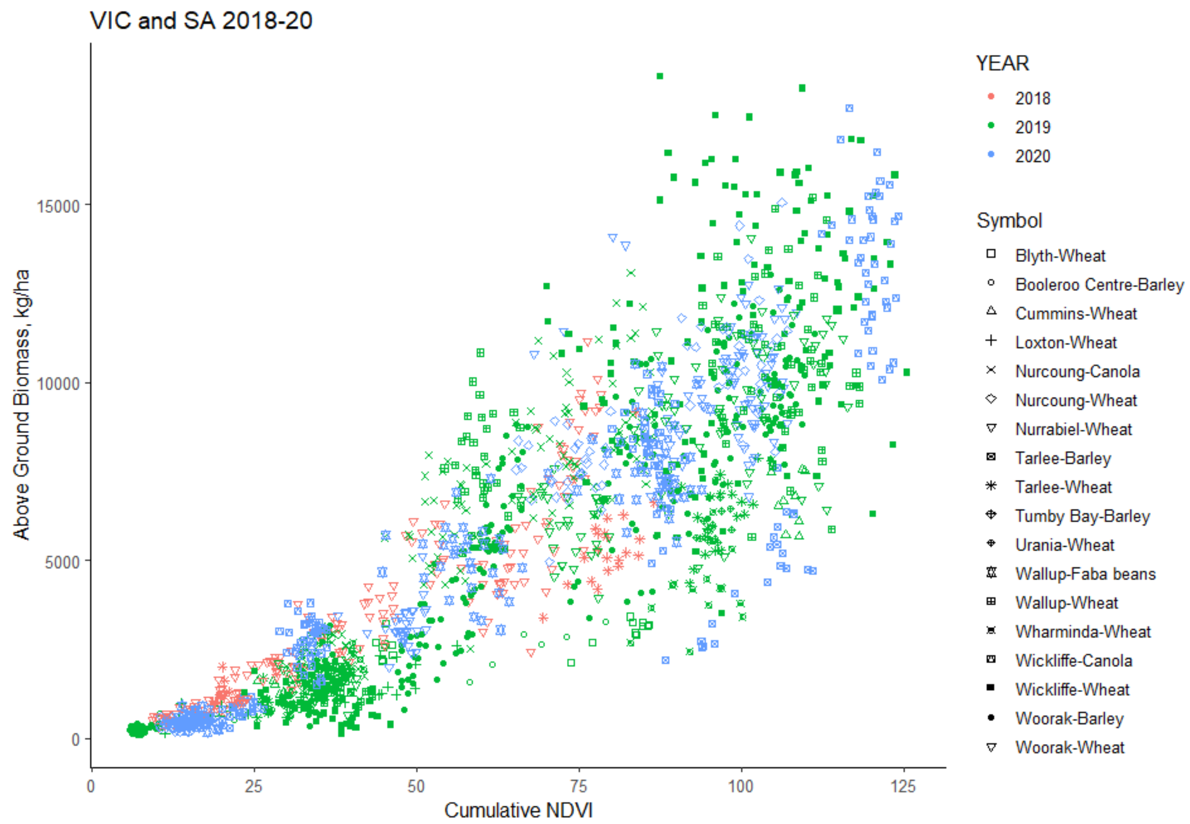

Figure 2. Corresponding cumulative NDVI and AGB (kg ha^{-1}) from biomass cuts (N = 2486), across multiple paddock, crops and years. The fitted regression results are presented in Table 1.

Table 1. Regression results for AGB (kg ha^{-1}) and cumulative NDVI.

Year	Location	Crop	N	Intercept	Slope	Adj. R^2	Std. Error
2018-20	VIC and SA	Wheat, barley, canola, legumes	2486	-1658.3	116.5	0.77	2056.2
2018	Woorak VIC	Wheat	162	-1043.7	110.2	0.84	1043.2
2019	Nurrabiel VIC	Wheat	120	-2604.8	119.6	0.82	1493.4
	Wallup VIC	Wheat	120	-1261.6	114.1	0.71	2210.5
	Wickliffe VIC	Wheat	160	-3543.0	149.9	0.71	3002.1
	Woorak VIC	Barley	243	-1511.9	107.4	0.84	1450.8
2020	Nurcoung VIC	Wheat	90	-1249.5	120.5	0.94	1091.7
	Woorak VIC	Wheat	336	-1316.8	116.6	0.91	1279.6

Discussion and Conclusions

There are numerous potential uses for spatial and temporal estimates of AGB. In agronomic research trials, the AGB could be estimated retrospectively between biomass cut dates, and/or provide biomass estimates continuously across the paddock. The linear regression results presented indicate that the best model fits are developed for specific paddocks, using biomass cuts at three or more dates through the season. The combined dataset results indicate that biomass can be estimated from previous trials, although the R^2 and standard error values may be poorer than relationships developed for a specific crop and season. The linear regression results are used to calculate AGB estimates on a per-pixel basis for multiple points in time throughout the crop season (either targeted at particular crop development stages or on a daily time step). These AGB time series enable the calculation of crop growth rates on a per-pixel basis across each paddock.

We are using contiguous spatial AGB and crop growth rate data, combined with soil, climate and crop management information, to understand the underlying physical, chemical and biological subsoil constraints on crop growth (e.g. soil type and/or soil nutrient profiles). A better understanding of the spatial distribution of these constraints, and their impact on crop growth, supports more cost-effective management of multiple soil constraints. We are also using the spatial estimates of AGB to estimate canopy nitrogen (N) and N requirements using an N dilution approach (Fitzgerald et al. 2010).

Further refinements of the estimation techniques are being developed. One of the drawbacks on the use of optical satellite imagery is the dependence on clear sky conditions. To fill in time gaps, other satellite imagery (e.g., Planet imagery, https://www.planet.com/) or ground-based active optical measurements can be calibrated to the Sentinel-2 imagery and directly substituted. We are planning to evaluate this surrogate sensor data to quantify the improvement when time gaps exist. Another refinement is to determine the requirements for biomass cuts needed to establish the relationships for a given paddock and crop; specifically, how many sample sites, the timing and frequency.

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