Hybridization of vegetation index with agroclimatic data to improve biomass estimation in tomato for precision N management

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Hybridization of Vegetation Index With Agroclimatic Data to Improve Biomass Estimation in Tomato for Precision N Management

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Abstract—**Crop biomass is an important parameter to be non-destructively monitored for the proper management of nitrogen (N) fertilization in vegetable cropping systems. The present paper aims at showing the development of an innovative vegetation index that integrates both reflectance measurements and growing degree days (GDDs) for biomass estimation in tomato under different N fertilization treatments. Along five growth stages of tomato plants, both the Green Vegetation Index (GVI) and the plant biomass were monitored. Then the cumulative area under the curve of the GVI of the crop across the GDDs (cIGVI) was calculated per each experimental plot and correlated with tomato biomass. Even though significant weak relationships between GVI and biomass were found at each growth stage, they cannot be used in intermediate periods since they are calibrated for a specific growth stage. The adoption of cIGVI significantly improved the biomass estimation in comparison to the simple GVI-biomass models, and the relationship with tomato biomass was found to follow a Gompertz function. These results suggest that cIGVI may be a promising index for estimating tomato biomass across the entire growing season under different N statuses, and including spectral data in agroclimatic model for estimating biomass can enhance the prediction performances.**

Keywords—precision nitrogen management, biomass estimation, reflectance, growing degree days, vegetation index

I. Introduction

Crop biomass is an essential parameter to be monitored for proper crop management in greenhouses and open field conditions. It is related to the general health status of the crop, and can also find application for the precise management of nitrogen (N). The critical N dilution curve is widely known among plant physiologists and agronomists: it relates the actual biomass of the crop with the critical N concentration (i.e., the minimal N concentration needed to maximize the actual biomass production) [1]. The simultaneous monitoring of both biomass and N concentration allows for the calculation of the Nitrogen Nutrition Index (NNI), where the supply of N should occur whenever the NNI falls below 1 [2]. NNI has been highly related to different vegetation indices (VIs) monitored by hand-held reflectance sensors for a diverse number of vegetable crops [3]. Although the relationship VIs-NNI is useful for determining the optimal moment for N

supply through fertigation, [4] highlighted that algorithms for optimal N rate adopting reflectance sensors are still lacking. By knowing the actual biomass of the crop and actual N concentration, the amount of N fertilizer to be applied to the crop can be easily calculated [2]. On the other hand, the direct measurement of both the biomass and N concentration in the crop is excessively time-consuming for the prompt application in N fertilization management, thus indirect estimates of both N and biomass are currently being explored by several authors. In greenhouse crop systems, actual biomass has been estimated by adopting several weather-based growth models. The Total Dry Matter (TDM) was estimated in cucumber by [5] through modeling the Leaf Area Index (LAI), the intercepted Photosynthetically Active Radiation (PAR), and the greenhouse CO_2 concentration, although overestimation occurred at the late developmental stage. In [6] a simple model that simulates the TDM was developed using the Product of normalized Thermal Time and PAR (PTTP) coupled with a photosynthesis model. Again, [7] developed the VegSyst model which simulates TDM, evapotranspiration, and N uptake by crops, adopting easily obtainable weather data to encourage its adoption on farms. These weather-based models are assuming an optimal nutritional status [7], even though it is notorious that N deficiency limits dry matter accumulation [8]. Therefore, the suitability of the meteorological predictors for estimating crop biomass when different N status occurs remains questionable. Reflectance measurements are useful for assessing both the N status [3] and estimating morphological parameters in greenhouse conditions. For instance, [9] used the reflectance at 460 nm for estimating the PAR interception and the LAI in sweet pepper and argued that the inclusion of reflectance into crop models could improve their efficiency. The Normalized Difference Vegetation Index (NDVI) was used by [10] to estimate rice biomass at panicle initiation. However, although estimating biomass in growth stages that are critical for N fertilization is of interest for cereals crops, it is less suitable for vegetable crops, where N can be virtually supplied at any moment of the growing cycle via fertigation. Thus, reflectance-based models for estimating biomass in vegetable crops should work at any moment of the crop cycle. Moreover, when biomass is estimated through traditional vegetation indices, the issue of saturation at a high biomass level is often experienced [11]. Some authors

proposed the adoption of cumulative vegetation indices for improving the estimation of crop biomass [11, 12]. Also, the integral of vegetation indices across the day of the year (DOY) resulted to be highly correlated with crop yield and biomass [11]. However, the use of DOY for calculating the integral of vegetation indices to estimate crop growth may limit their applicability in different locations, given that plant development depends on climate factors (e.g., temperature), which are not accounted for by the merely temporal indicators [13]. Thus, combining spectral information with agroclimatic data is of interest for estimating crop biomass. From the previous work of [14], the Green Vegetation Index (GVI) resulted to be the most adequate for assessing the potential yield and N status in tomato. Therefore, the present paper aims at illustrating the development of an innovative vegetation index based on the integration of the GVI with the Growing Degree Days (GDDs) for biomass estimation of tomato crops across the entire growing season.

II. MATERIALS AND METHODS

A. Experimental design

The experiment was set up in the summer of 2022 at the University of Bologna experimental farm in Cadriano, Italy. Tomato (*Solanum lycopersicum* L.) was transplanted in open-field in a single-row cropping system at 27,700 plants ha^{-1}. Three N treatments were supplied with three replicates in a randomized block design, consisting of different percentages (0, 60, and 100%) of total crop N requirement (N0, N60, N100). The total N crop requirement was calculated through the balance sheet method [15] using the critical N uptake of 2.24 kg N t^{-1} reported by [16]. Ammonium nitrate was supplied 6 times through fertigation, following the crop N uptake rate. During the growing season the N uptake rate was: 6% of N total uptake up to 28 days after transplanting (DAT), 78% from 29 to 77 DAT, and 16% from 78 to 105 DAT [17]. Crop water requirements were fulfilled with drip irrigation according to the water balance sheet method, maintaining the soil moisture at the field capacity [18]. The computation of ET_c adopted the single Kc method, and the ET_0 was estimated through the Hargreaves-Samani equation [19]. P_2O_5 was applied before transplanting at 85 kg ha^{-1}, while a starter dose of 20 kg ha^{-1} of K_2O was supplied through fertigation. The crop was transplanted on a loamy-clay soil with the following main characteristics: pH=7.1, Total lime ($CaCO_3$) =18 g kg^{-1}, Electrical conductivity=0.07 mS cm^{-1}, Organic Matter=1.43%, Total N=0.9 g kg^{-1}, Assimilable P=50 mg kg^{-1}, Exchangeable K=171 mg kg^{-1}, Cation Exchange Capacity= 10.8 cmol kg^{-1}. Two plants per plot were sampled for total above-ground biomass determination in five growth stages at 264, 386, 598, 859, and 1125 growing degree days °C (GDDs), henceforth shortened as T1, T2, T3, T4, and T5. GDDs were calculated according to [20], using 30 and 10 °C as T_{max} and T_{basal}, respectively.

B. Description of the vegetation indices

Before sampling, the reflectance of each plant was monitored with a portable multispectral passive radiometer (Spectrosense 2+, Skye, UK) in the band of green (560 nm), and Near Infrared (NIR) (810 nm), to enable the calculation of the GVI as the simple ratio between the NIR (R810) over the green (R560) reflectance as shown in (1):

$$GVI = R810/R560 \qquad (1)$$

Moreover, an innovative vegetation index is proposed in this manuscript, which has been developed by integrating the multitemporal monitoring of the GVI with the GDDs. The GVI monitored was plotted against the GDDs. The pattern of the GVI is strictly dependent on the N status, where a higher N supply implies a higher value of the GVI. Therefore, it is reasonable to consider the area under the curve to be dependent on the N status, and thus it could also be a predictor of the biomass. The area below the curve between two monitoring dates can be approximated to a trapezoid, represented as the shaded area in Fig. 1, henceforth named Integral GVI (IGVI), and can be calculated accordingly (2):

$$IGVI_{Tn}= (GVI_{Tn} + GVI_{Tn-1})(GDD_{Tn}-GDD_{Tn-1})/2 \qquad (2)$$

The biomass accumulation is a cumulative function and depends on the global crop health status from the planting date [21]. Therefore, it can be linked to cumulative vegetation indices, such as the *Cumulative IGVI (cIGVI)* over the sampling time shown in (3).

$$cIGVI =\sum IGVI_{Tn} \qquad (3)$$

Thus, the cIGVI has been calculated per each experimental plot for each sampling date, and it was then related to the monitored biomass.
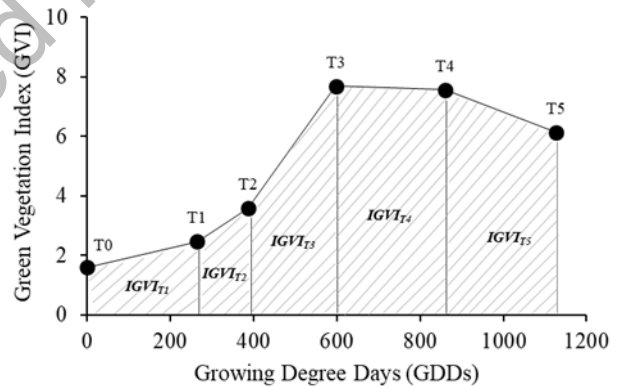
Fig. 1. Pattern of GVI across growing degrees days and representation of the IGVI$_{Tn}$ between two monitoring date

C. Statistical analysis

ANOVA analysis was carried out with R studio software (version 4.2.0) to assess the differences in biomass among N treatments at each sampling date. The assumption of normality and homoscedasticity was checked using the Shapiro-Wilk test and Levene test respectively. Linear regression analysis was used to find a correlation between GVI and plant biomass, while nonlinear regression analysis between cIGVI and biomass was carried out. The assumption of normality distribution and homoscedasticity of residuals was checked. In case such assumptions were not met the log-log transformation was performed, by calculating the natural logarithm for both variables. The nonlinear model for fitting data was chosen using the software CurveExpert Basic (version 2.2). Performance assessment metrics, namely Root

Mean Square Error (RMSE), Percentage RMSE (%RMSE), and R^2, were computed.

III. RESULTS

N treatments resulted in a significant difference in biomass production across GDDs, except at T4 where no significant differences were observed (Fig. 2). Plants grown under the full N rate (N100) exhibited a faster growth compared to N60 and N0, particularly at T1 and T2. However, at T3 and T5, only the differences between N100 and N0 were statistically significant. Consequently, it is not possible to utilize a single growth curve based on GDDs to estimate biomass accurately for different N statuses. Indeed, adopting a single model based on GDDs would overestimate biomass when N is deficient and could underestimate it when N requirements are fully met. The linear regression analysis between GVI and plant fresh biomass proved to be significant at T1, T3, and T5, while it resulted not significant at T2 and T4 (Table 1). The determination coefficient (R^2) was influenced by the growth stage, as well as the slope and intercept of the linear relationship. Consequently, different linear relationships were established to estimate tomato biomass. The RMSE values in Table 1 tended to increase with an increase in GDDs, whereas the Percentage RMSE (%RMSE) did not exhibit a corresponding variation. Notably, the global RMSE and global %RMSE values in Table 1 did not include the data from growth stages T2 and T4, as the relationships between GVI and biomass were not found to be significant. Additionally, the relationships between the cIGVI and plant fresh biomass was examined, resulting in a sigmoidal growth curve (Fig. 3). The dashed line in Fig. 3 represents the fitted model based on the Gompertz function, which comprises three highly significant coefficients (a, b, k) obtained from nonlinear regression analysis (p < 0.05).

$$Biomass = a \; e^{-e^{(b \, - \, k \, cIGVI)}} \qquad (4)$$

Where e is the Euler number, *a* is a coefficient corresponding to the asymptote of the sigmoidal and is equal to 7507 g, *b* is the location parameter related to the intercept of the curve equal to 0.000519, and *k* is related to the growth rate of the curve, which is equal to 1.67.

Table 1 Slope and intercept of linear models between GVI and plant biomass (g plant^{-1} FW) at different growth stages. Root mean square error (RMSE), %RMSE and R^2 are also reported. Global RMSE and %RMSE are calculated considering the data of each growth stage, excluding T4 (n=18).

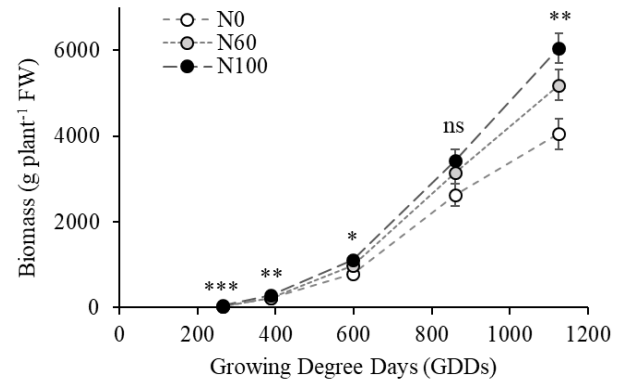|	**T1**	**T2**	**T3**	**T4**	**T5**	**Global**
GDDs	264	386	598	859	1125	
slope	35	49.9	116	19.4	778	
intercept	-39.3	70.1	244	2946	1143	
R^2	0.52	0.18	0.52	0.001	0.37	
RMSE	10.4	50.6	171	865	1024	599
%RMSE	28.8	26.6	22.1	27.9	29.8	27.1
	***	ns	***	ns	**	

Fig. 2. Evolution of the plant fresh weight (FW) biomass across GDDs.

The RMSE of the Gompertz model (Fig. 3) is lower in comparison to the global RMSE calculated for the linear relationships between GVI and plant biomass (Table 1), although the %RMSE is significantly higher. The model relating cIGVI and biomass enables the inclusion of all treatments in the fitting procedure, which was not feasible using interpolation with GDDs (Fig. 2). This is due to variations in the observed biomass as determined by the analysis of variance (ANOVA) for different nitrogen treatments. However, the residuals of the Gompertz models resulted to be non-normal according to the visual interpretation of the Q-Q plot. In addition, the residuals also tend to increase as the cIGVI increases, thus revealing a strong heteroscedasticity. To fulfill the assumptions of normality and homoscedasticity of residuals, a log-log transformation was applied. The transformed data were then fitted with a second-order polynomial curve (Fig. 4), which yielded highly significant results in the nonlinear regression analysis and satisfied the assumptions of normality and homoscedasticity of residuals. Even though the transformed model slightly increased the RMSE in comparison to the Gompertz model from 482 to 526 g plant^{-1}, the %RMSE is significantly improved in the transformed model and it was reduced from 132% (Fig. 3) to 22.8% (Fig. 4).
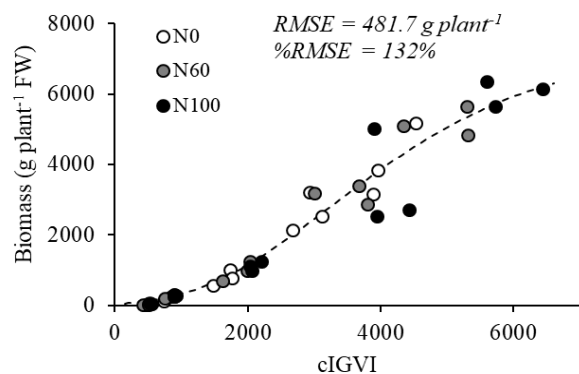

Fig. 3. Relationship between cIGVI and fresh plant biomass (FW). The dashed line represents the fitted model according to the Gompertz function (n=45).
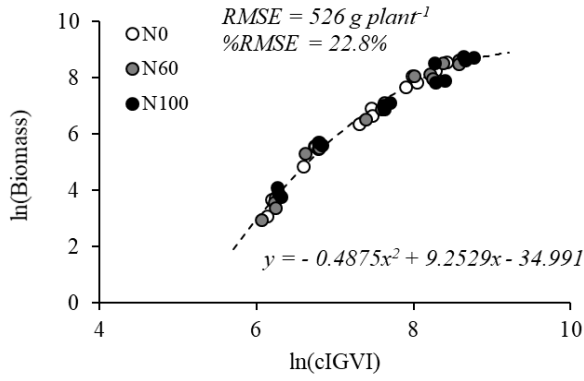
Figure 4 Model for estimation of the natural logarithm of biomass according to the natural logarithm of cIGVI

Figure 5 Distribution of Percentage Error of the two models (Gompertz, and log-log transformed) in relation to the measured biomass.

When the non-transformed model was utilized during the early stage of the growing season, an overestimation was observed. However, this overestimation was avoided when the log-transformed model was employed (Fig. 5). As the biomass level increased, the error of estimate for the non-transformed model became comparable to that of the log-log transformed model.

IV. DISCUSSION

The estimation of crop biomass is of significant importance for precision N management. This estimation enables the virtual replication of the critical N dilution curve and facilitates the identification of the optimal timing and rate of N fertilizer application [2]. Biomass accumulation is a cumulative process that is strictly dependent on the N status. Thus, the attempt to estimate plant biomass according to GDDs will fail if N status is not considered (Fig. 2). Given GVI has been evaluated as the best vegetation index for assessing non-destructively the N status and forecasting the yield in processing tomato [14], its ability in estimating tomato biomass has been explored in this paper. GVI is linearly related to plant biomass at all growth stages (Table 1), except at T2 and T4, probably determined by the lacking of significant differences in biomass among N treatments at the T4 stage (Fig. 2). Despite these correlations, linear models are calibrated for a specific growth stage, and they cannot be adopted in intermediate moments of the crop cycles thus limiting the applicability for vegetable farming, where N could be supplied in any moment of the growth cycle via fertigation. Moreover, the prediction accuracy of the linear relationships between GVI and plant biomass across GDDs is considered low for a prompt application in precision N strategies (harmonic mean of $R^2=0.45$). An innovative vegetation index is here developed, that combines the spectral properties of the crop with GDDs. The cumulative Integral Green Vegetation Index (cIGVI), defined as the cumulative area under the GVI curve over GDDs (Fig. 1), exhibited a strong correlation with crop biomass. This relationship followed a Gompertz curve (Fig. 4). The Gompertz function has been widely adopted for describing growth phenomenon across time [22], including plant biomass [23]. The mathematical derivation of cIGVI allows us to recognize the added value of such an index. Indeed, the inclusion of GDDs into the formula of cIGVI permit estimating the plant biomass at any moment of the crop cycle.
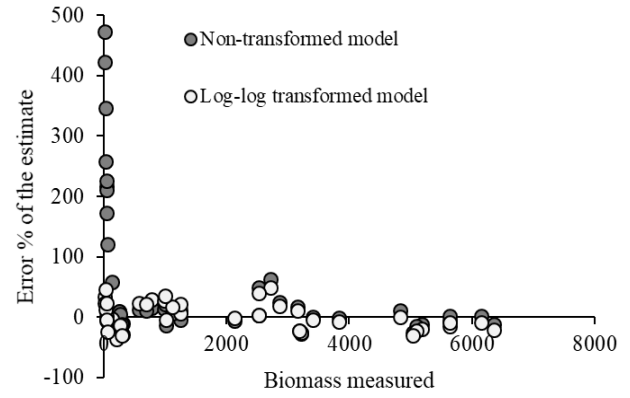
Moreover, the simultaneous inclusion of GVI into the formula allows us to consider the crop N status in the estimation process, thus overcoming the limits imposed by the use of models based on solely GDDs. Although the cIGVI-biomass model reported a lower RMSE in comparison to the global RMSE of the linear relationships between GVI and biomass, the %RMSE heavily increased from 27.1% (Table 1) to 132% (Fig. 3). This is due to an overestimation of the biomass at the low value of cIGVI (Fig. 5). Hence, by applying the logarithmic transformation to the model, the Percentage RMSE (%RMSE) was reduced to 22.8%, effectively preventing any overestimation during the initial stage of the growing season. The proposed model for precise N management becomes of utmost importance in ensuring accurate biomass estimation during the initial stage of the growing season. This significance arises from the fact that tomato plants experience exponential growth (Fig. 3) during this critical period, leading to an increased requirement for N. The cIGVI has some similarities with other vegetation indices developed by previous authors. The cumulative Simple Ratio over time was related with crop yield and biomass by [12], improving the estimation performance in comparison to the same vegetation index in the non-cumulative form. Again, [11] demonstrated that the use of integral of VIs across time (day of the year) improves biomass estimation compared to simple VIs, overcoming the common issue related to the saturation effect at the highly-dense canopy. In accordance with the finding of this paper, [24] combined the crop optical properties (RGB) with agroclimatic data (GDDs) for crop biomass estimation, finding an improvement when GDDs were considered alone. This paper demonstrated that including the spectral information in agroclimatic data improved the biomass estimation, and can be of interest for greenhouse cropping systems where weather-based models are mainly adopted. However, despite the promising potential of cIGVI in estimating tomato biomass (Fig. 5), it should be noted that only a one-year experiment on a single location was considered. A second-year experiment is recommended (and currently underway) to validate the model and to test its adaptability to different cultivars. Different vegetation indices are recommended to be tested, as well as different nonlinear functions to assess whether the overestimation at the early stage of the growing season can be overcome.

V. Conclusions

The estimation of crop biomass across the entire growing season is of interest for accurate N management in vegetable cropping systems. The findings of this study demonstrate that biomass estimation solely based on the traditional Growing Degree Days (GDDs) model is inadequate when different nitrogen (N) statuses are present. Therefore, to enhance biomass estimation, it is crucial to incorporate optical properties that are associated with specific nutritional conditions. The cIGVI is a hybrid vegetation index that combine the crop spectral properties (GVI) with agroclimatic data (GDDs) that resulted to be highly related to tomato biomass. The use of the cumulative cIGVI significantly enhanced the accuracy of biomass estimation compared to the traditional GDDs approach. This improvement was attributed to the capability of the cIGVI to incorporate all the nitrogen (N) treatments within a single model, which was not possible with the GDDs-based model. Also, the model based on cIGVI allows to estimate tomato biomass at any moment of the growing season, which is otherwise not possible when specific linear models based on simple vegetation index (GVI) are adopted. However, to improve the biomass estimation, especially at the early stage of the growing season, the logarithmic transformation of the monitored cIGVI is needed. A simple transformation does not imply any alterations to the meaning of the equation found in this article. In fact, given that we are dealing with a system, the plant, that grows exponentially makes it necessary to undergo a logarithmic transformation. Although further experiments should validate the relationship between cIGVI and biomass, the index here developed is promising for being adopted in vegetable cropping systems. The integration of spectral information to agroclimatic data enhanced the biomass estimation in open field, and may be an opportunity for greenhouses cropping systems.

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