Scientific Papers. Series E. Land Reclamation, Earth Observation & Surveying, Environmental Engineering. Vol. VI, 2017
Print ISSN 2285-6064, CD-ROM ISSN 2285-6072, Online ISSN 2393-5138, ISSN-L 2285-6064

MONITORING VEGETATION PHENOLOGY IN THE BRAILA PLAIN USING SENTINEL 2 DATA

Violeta POENARU[1,2], Alexandru BADEA[1], Iulia DANA NEGULA[2], Cristian MOISE[2]

[1]Romanian Space Agency, 21-25 Mendeleev Str., District 1, Bucharest, Romania
[2]University of Agronomic Sciences and Veterinary Medicine of Bucharest, 59 Marasti Blvd, District 1, Bucharest, Romania

Corresponding author email: violeta.poenaru@rosa.ro

Abstract

The continuous crop condition monitoring at a regional scale is critical especially for private investors which should apply land reclamations measures regarding the soil degradation and modern methods of irrigation for optimizing the water use efficiency and crop yield production. Benefiting from the newest European remote sensing technology, in particular the Sentinel 2 imagery, the paper investigates the crop vegetation status during the 2016's growing season and covers the Cazasu agricultural area, located in the Braila Plain. Red edge bands have been exploited in order to correlate the spectral indices with chlorophyll and the plant water content. Thus, the wheat biophysical variables, as leaf area index (LAI), leaf chlorophyll (CAB), canopy water content (CWC), normalized differential vegetation index (NDVI), fraction of vegetation cover (FCOVER) and fraction of absorbed photosynthetically active radiation (FAPAR) have been retrieved by inversion of PROSAIL canopy radiative transfer model. This model, focused on the red edge which stimulates the whole spectro-directional canopy field between red and near infrared, is sensitive to the variations in leaf chlorophyll, leaf area index, soil substrate and atmospheric conditions. A good synergy between vegetation variables was obtained, confirming the Sentinel 2 capabilities to monitor crops and to develop useful products to be offered as services to the farmers.

Key words*: crop vegetation status, Sentinel 2 data, vegetation biophysical parameters, Cazasu agricultural area*

INTRODUCTION

The launch of Sentinel 2 satellites offers new opportunities for a continuous monitoring of the land and vegetation in the context of the global warming and climate changes from the last decade. Since it provides continuity for the SPOT and Landsat missions, the red edge spectral band is useful in the estimation of plant chlorophyll content, biomass and hydric status.
Based on the hyperspectral remotely sensed imagery, the methodology for extracting red edge position parameters has been developed. The linear interpolation is the simplest method that assumes thereflectance red edge simplified to a straight line centred on a midpoint between maximum and minimum of the chlorophyll reflectance curve (Baret et al., 1987; Guyot et al., 1992; Danson and Plummer, 1995).
The second technique uses an inversion of Gaussian function for fitting the spectral reflectance in the 680 – 800 nm band range in order to determine its parameters (Bonham – Carter, 1988; Miller et al., 1990; Pu et al., 2003). Third method implies the forcing of Lagrange interpolation curve trough the given points fixed in the red edge spectrum bands (Dawson and Curran, 1988). The polynomial fitting method uses a high-order polynomial function to fit the reflectance spectrum between red edge position in the points corresponding to the minimum in red and maximum in NIR (Demetriades – Shah et al., 1990; Clevers and Jongschaap, 2001; Pu et al., 2003; Baranoski and Rokne, 2005).
Linking these methods into PROSAIL canopy radiative model allowed us to retrieve vegetation biophysical parameters from multispectral imagery (Jacquemoud et al., 1995). Thus, the canopy is considered a turbid medium with the leaves randomly located and having proper structural and chemical characteristics (Jacquemoud et al., 2009). Moreover, the model is best suitable for use in homogeneous vegetation canopies like wheat, rice and grassland and it has been widely validated by thescientific community (Verhoef, 1984; Thorp et al., 2012; Vuolo et al., 2009).

The transfer radiative models require three sub-models describing:(i) the leaf optical properties (e.g. leaf area index, mesophyll structure parameters, leaf chlorophyll, dry matter content, relative water content, brownpigment content and fraction of pure vegetation); (ii) the scattering and absorption processes within the canopy (solar zenith angle, fraction of diffuse incoming radiation and view zenith angle) and (iii) the spectral reflectance of the underlying soil background.

Different inversion strategies have been developed to reduce the number of variables and physical processes (Jacquemoud et al., 1995; Gastellu-Etchegorry et al., 2003; Rummelhart et al., 1986; Bacour et al., 2006; Mridha et al., 2014; Durbha et al., 2007). Among these approaches, look-up table (LUT) and artificial neural networks are computationally more efficient and can be applied on a pixel basis of satellite images to the most sophisticated models without any simplifications. The fundamental concept of neural networks consist in calibrating an inverse model over the synthetic learning dataset which can incorporate a priori knowledge of the measurement conditions like soil reflectance, canopy architecture and solar position. This implies a dataset selection (biophysical variables as inputs and outputs) in the generation of a training database that is accomplished by defining an optimal structure, normalization and calibration. Their main advantage is that to represent a good compromise between the level of accuracy and the complexity of setting-up the simulation. Thus, good agreement between global neural networks and interpolated ones has been obtained in the Sentinel 2 dataset case (Vuolo et al., 2016).

The Sentinel 2 satellites provide high spatial and temporal resolution data for assessing crop status and supporting agro-practices at the parcel level. Benefiting from the availability of Sentinel 2 data, many services can be developed in the agricultural sector. GEOFARM project, a service for agricultural monitoring in Romania, is dedicated to irrigation water management user community and aims to become a national advisory system for irrigated perimeters. Therefore, the objective of the paper is to perform an analysis of PROSAIL model inversion by artificial neural network approach and, in the same time, to derive biophysical parameters such as leaf chlorophyll content, canopy water content and leaf area index of wheat crops from multispectral Sentinel 2 data. In this perspective, the synergic analysis through satellite data and agro-models allows the end-user to determine an optimal input for each affected area inside the plot, according to intra-parcel variability.

MATERIALS AND METHODS

Description of the test area and dataset

The study area is located in Braila Plain, North Braila Terrace subunit, Romania (latitude $45^0$12’58” to $45^0$21’03”, longitude $27^0$42’54” to $27^0$57’36”). It covers an area of 25,000 ha and extends into the western part of Braila town (Figure 1). The plains generally predominate, with some dunes in the northern part which do not exceed 40 m in elevation with a slope ranging from 1^0 to 3^0.

Geologically, the area lies on loess-like deposits, fluvial and aeolian deposits combined with gravels and sands which date back to the quaternary period.

The climate is temperate continental characterized by hot and dry summers, low rainfall (400 – 490 mm), cold winters without a stable and continuous snow cover, influenced by the Siberian anticyclone.

High temperatures in the summer season favour the increase of the saturation deficit which induces the intensification of the evaporation process. The dominant crops are wheat, corn, sunflower, sugar beet, alpha-alpha, rapeseed and vegetables.

The investigations were focused on wheat biophysical parameters retrieval from multi-temporal multispectral Sentinel 2 data. We used 21 satellite images covering the phenological cycle of wheat crop from 2015-2016 seasons to estimate plant parameters with PROSAIL model. The Sentinel 2 top of canopy reflectance images were downloaded through Copernicus Open Access Hub (https://scihub.copernicus.eu/).

The pixels contaminated with clouds/cloud shadow were not used in this study. A set 41 of samples were randomly selected from the centre of wheat parcels, one sample representing a group of 5 x 5 pixels.

Biophysical parameters retrieval methodology

Leaf area index defined as the one sided green leaf area per unit ground surface area is a key variable when modelling surface evapotranspiration and biomass production (Watson, 1947, Dorigo et al., 2007). FCOVER corresponds to the gap fraction in the nadir direction and represents the amount of vegetation distributed in the horizontal plane. This parameter is used to separate vegetation and soil in the energy balance processes (Baret et al., 2005). FAPAR corresponds to the fraction of photosynthetically active radiation absorbed by the canopy and is included in the agro-models to derive the biomass accumulated during a given period (Baret et al., 2005). Canopy chlorophyll content (Cab) is a bio-indicator of plants actual health status and of a vegetation gross primary productivity (Jaramaz et al., 2013). It can be expressed as leaf area index multiplied by leaf level chlorophyll content. Canopy water content (CWC) defined as mass of water per unit ground area is a dynamic parameter that depends on the balance between water losses from transpiration and water uptake from the soil (Ustin et al., 2012). It can be also expressed as leaf area index multiplied by equivalent water thickness (Jacquemoud et al., 1990).

To derive these parameters, we used the algorithm included in the SNAP ESA Toolbox that generates a comprehensive database of vegetation characteristics and top of canopy (TOC) reflectance. Neural networks were afterwards trained to estimate the canopy characteristics from the TOC reflectance along with the corresponding angles defining the observational configuration. For each biophysical variable, one particular neural network was calibrated. Each neural network is composed of: one input layer containing a set of 11 normalized data, one hidden layer with 5 neurons with tangent sigmoid transfer function (to activate the artificial neurons) and one output layer with linear transfer function (Vuolo et al., 2016) (Figure 2). Leaf area index, FCOVER, FAPAR, Cab and CWC were finally retrieved (Table 1).

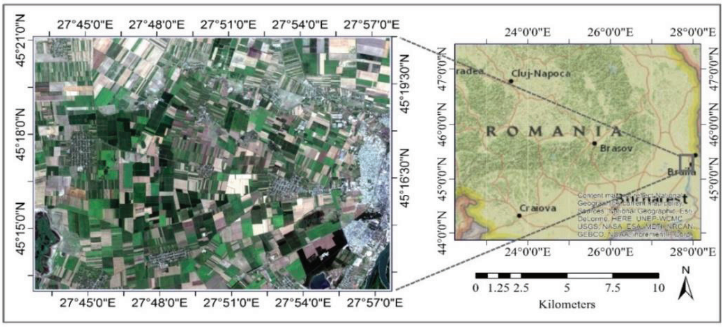

Figure 1. Cazasu agricultural area, Romania

Tabel 1. Specific ranges for biophysical variables retrieved from the PROSAIL model

Parameter	Main indicator	Unit	Min	Max	stdv
Leaf area index	Plant functioning	m^2m^{-2}	0	23	0.023
Leaf chlorophyll content	Nitrogen stress/ photosynthesis	$\mu g\ cm^{-2}$	-110	546	0.6
Canopy water content	Drought stress	$Kg\ m^{-2}$	-0.32	0.22	0.005
FCOVER	Plant development	-	0	0.98	0.002
FAPAR	Photosynthesis	-	-1.46	0.94	0.02
NDVI	Nitrogen stress/ drought stress	-	-0.3	0.88	0.0012
Sun zenith	Surface albedo	Angle degrees	28	69	-
Sun azimuth	Surface albedo	Angle degrees	147	168	-

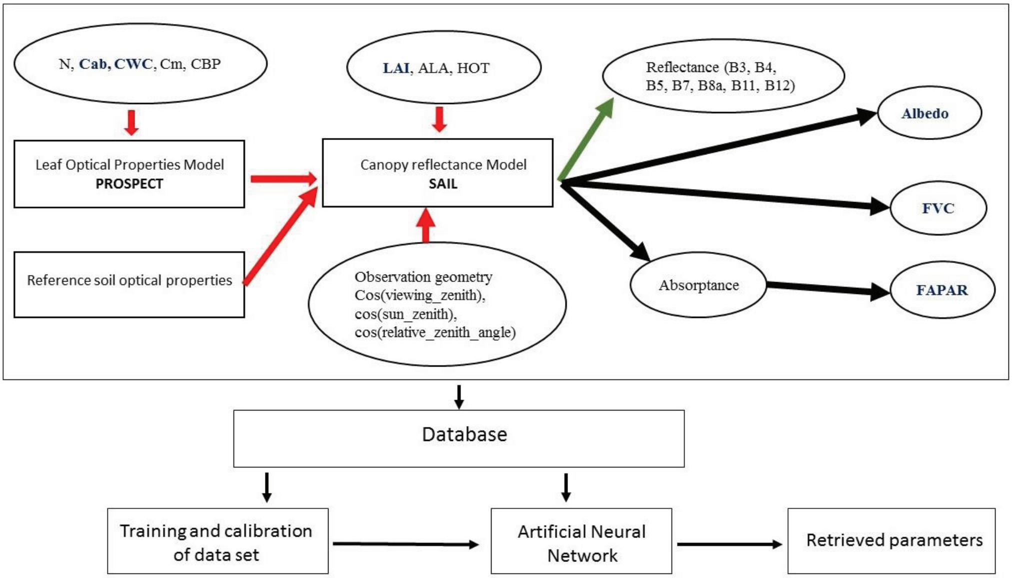

Figure 2. Schematic presentation of the PROSAIL model in forward mode

RESULTS AND DISCUSSIONS

The PROSAIL model analysis

The current study presents preliminary results of Sentinel 2 data processing for biophysical parameters estimation without validation on in-situ measurements. Therefore, the PROSAIL model included in SNAP software as biophysical processor was used in this analysis. We first verified that the Sentinel 2 surface reflectances are consistent at spatial resolution. After resampling, the PROSAIL model was applied to all the data used for neural networks, normalization, quality flags and uncertainties processing steps disposed in the SNAP parameter tables (Algo_S2_V2.1_SL2T_biophysical_parameter. xlsx, © ESA version 5.04). Each table contains the weights, biases and neural network structure information that are settled to the certain values which are evaluated when the model is running. The uncertainties associated to the inputs and the algorithm calibrations were reduced by applying rules which consider the valid value (Table 2).

The biophysical parameters evaluation

The retrieved biophysical variables are presented in Figure 3. Mean and standard deviation, the minimum and maximum value and the coefficient of variation were inspected to ensure the parameter value is in definition range (Delegido et al., 2011; Vuelo et al., 2016, Frampton et al., 2013).According to the number of samples, the plots were divided in 2 data sets. The statistical analysis was done separately for each dataset.

We considered an average of the best fitted spectrum. The results shown in Figure 4 depict a good agreement between LAI – FCOVER, FCOVER – FPAR, LAI - Cab and LAI – CWC (with a correlation coefficient above 0.90). Normalized differential vegetation index was computed from Sentinel data in order to validate LAI results. As is observed in Figure 4, this estimation remains in agreement with previous studies based on the same tools (Gaman et al., 1995; Barman et al., 2009).

Table 2. Rules for artificial neural network selection

Description of the threshold	Value
Input is out of definition domain	1
Output is lesser than minimum output, but within the tolerance	2
Output is greater that maximum output, but within tolerance	4
Output is too low	8
Output is too high	16
Bias	Up to 4

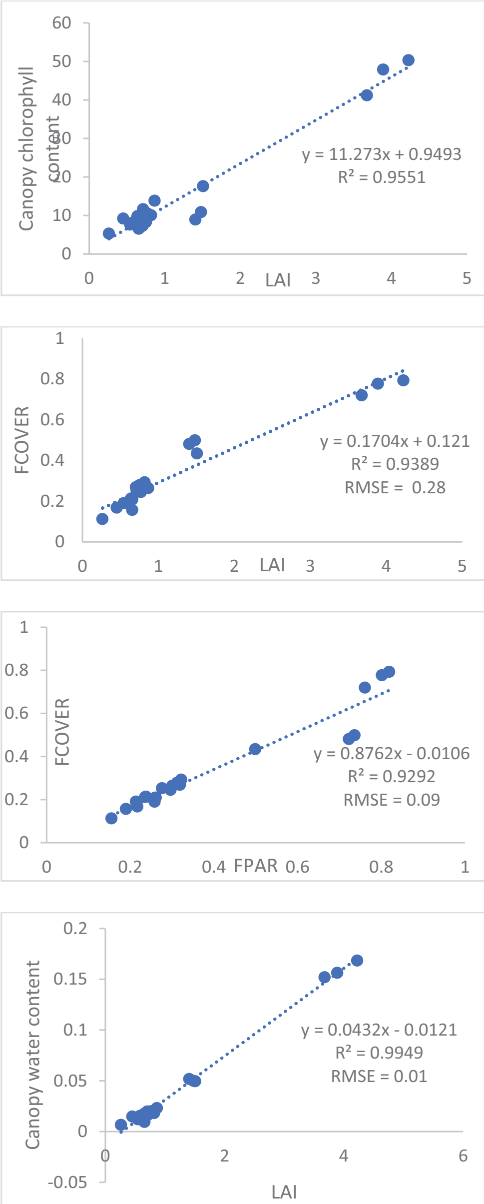

Figure 3. Biophysical variables based on averaged subplots

CONCLUSIONS

The study assesses the sensitivity of Sentinel 2 data to estimate wheat biophysical variables using PROSAIL model in a homogenous area from the Braila Plain. For the fast model inversion, an artificial neural network included in the SNAP biophysical processor was used.

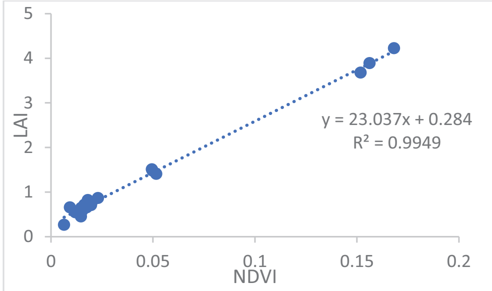

Figure 4. Relationship between LAI and NDVI

LAI, FCOVER canopy water content and leaf chlorophyll content have been estimated without in-situ validation measurements.

The good correlation between these variables demonstratesthe Sentinel 2 capabilities to monitor crops and to develop useful products to be offered as services to the farmers.

The future activities will be focused on the integration of vegetation biophysical parameters into a WebGIS environment givingend usersthe possibility to visualize and query the crop information at different dates during the growing season.

ACKNOWLEDGEMENTS

Sentinel 2 data were downloaded from COPERNICUS Scientific Hub. This work was performed with the support of Romanian Space Agency and it is financed by the Project PN II Partnerships No171/2014.

REFERENCES

Bacour C., Baret F., Béal D., Weiss M., Pavageau, K., 2006. Neural network estimation of LAI, fAPAR, fCover and LAIxCab, from top of canopy MERIS reflectance data: principles and validation. Remote Sensing of Environment, 105, 313-325.

Baranoski G.V.G., Rokne J.G., 2005. A practical approach for estimating the red edge position of plant leaf reflectance. International Journal of Remote Sensing, 26, S. 503-521.

Baret F., Champion I., Guyot G., Podaire A., 1987. Monitoring wheat canopies with a high spectral resolution radiometer. Remote Sensing of Environment, 22, pp. 367–378.

Baret, F.,Pavageau, K., Béal, D., Weiss, M., Berthelot, B., Regner, P., 2005. Algorithm Theoretical Basis Document for MERIS Top of Canopy Land Products (TOC_VEG). Contract ESA AO/1-4233/02/I-LG, INRA &Noveltis, Avignon.

Barman,,D., Kalra, N., Sahoo, R.N., Chakraborty, D., Kamble, K., 2009. Deriving Homogeneous Soil Fertility Unit through GIS for Site Specific Nutrient Management by QUEFTS model, Fourth World Congress on "Conservation Agriculture", Feb 4-7, New Delhi, India.

Bonham-Carter G., 1988. Numerical procedures and computer program for fitting an inverted Gaussian model to vegetation reflectance data. Computers and Geosciences, 14, pp. 339–356.

Clevers J., Jongschaap R., 2001. Imaging spectrometry for agricultural applications. In Imaging Spectrometry. Basic principles and prospective applications, F. van der Meer and S. de Jong (Eds) (Dordrecht: Kluwer), pp. 157–199.

Danson F., Plummer S., 1995. Red edge response to forest leaf area index. International Journal of Remote Sensing, 16, pp. 183–188.

Dawson T.P. and Curran P.J., 1998. A new technique for interpolating red edge position. International Journal of Remote Sensing, 19(11): 2133-2139.

Delegido, J., Verrelst, J., Alonso, L., Moreno, J., 2011. Evaluation of Sentinel-2 Red-Edge Bands for Empirical Estimation of Green LAI and Chlorophyll Content. Sensors (Basel, Switzerland), 11(7), 7063–7081.

Demetriades-Shah T., Steven M.D., Clark J.A., 1990. High resolution derivative spectra in remote sensing. Remote Sensing of Environment, 33, pp. 55–64.

Dorigo, W.A.,Jurita-Milla, R., de Wit, A.J.W., Brazile, J., Singh, R., Schaepman, M.E., 2007. A review on reflective remote sensing and data assimilationtechniques for enhanced agroecosystem modeling. Int. J. Appl. Earth Obs. Geoinf. 9(2), 165–193.

Durbha S.S., King R.L., Younan N.H., 2007. Support vector machines regression for retrieval of leaf area index from multiangle imaging spectroradiometer. Remote Sens. Environ., 107:348–61.

Frampton, W. J., Dash, J.,Watmough, G., Milton, E. J., 2013. Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 82, 83-92.

Gamon, J.A., Field, C.B., Goulden, M.L., Griffin, K.L., 1995. Relationship between NDVI, canopy structure and photosynthesis in three California vegetation types. EcolAppl 5:28–41.

Gastellu-Etchegorry J.P., Gascon F., Esteve P., 2003. An interpolation procedure for generalizing a look-up table inversion method. Remote Sens. Environ., 87 (1), pp. 55–71.

Guyot G., Baret F. and Jacquemond S., 1992. Imaging spectroscopy for vegetation studies. In Imaging Spectrometry: Fundamentals and prospective applications, F. Toselli and J. Bodechtel (Eds) (Dordrecht: Kluwer), pp. 145–165.

Jacquemoud S., Baret F., Andrieu B., Danson F. M., Jaggard K., 1995. Extraction of vegetation biophysical parameters by inversion of the PROSPECT+SAIL model on sugar beet canopy reflectance data — Application to TM and AVIRIS sensors. Remote Sensing of Environment, 52, 163−172.

Jacquemoud S., Verhoef W., Baret F., Bacour C., Zarco-Tejada P.J., Asner G.P., François C., Ustin S.L, 2009. PROSPECT+SAIL models: A review of use for vegetation characterization. Remote Sens. Environ., 113, 56–66.

Jacquemoud, S., Baret, F., 1990. Prospect – a model of leaf optical-properties spectra. Remote Sens Environ 34:75–91.

Jaramaz, D., Perovic, V., Belanovic, S., Saljnikov, E., Cakmak, D., Mrvic, V., Zivotic, L., 2013. The ESA Sentinel-2 mission vegetation variables for remote sensing of plant monitoring. 2nd Int. Sci. Conf. RESPAG 2013, 950-961.

Miller J.R., Hare E.W., Wu J., 1990. Quantitative characterization of the red edge reflectance. An invertedGaussian reflectance model. International Journal of Remote Sensing, 11(10): 1755-1773.

Mridha N., Sahoo R. N., Kumar D. N., Sehgal V. K., Krishna G., Pradhan S., Gupta V. K., 2014. Genetic algorithm based inversion modelling of PROSAIL for retrieval of wheat biophysical parameters from the reflectance data. J. Agric. Phys., 14(1), 87–95.

Pu R., Gong P., Biging G.S., Larrieu, M.R., 2003. Extraction of red edge optical parameters from Hyperion data for estimation of forest leaf area index. IEEE Transactions on Geoscience and Remote Sensing, 41(4): 916-921.

Rummelhart D.E., Hinton G.E., Williams R.J., 1986. Learning internal representations by error propagation. In D. Rummelhart, & J. Mc Clelland (Eds.), Parallel data processing (pp. 318-362). Cambridge, MA (USA): M.I.T. press.

Ustin, S.L., Riaño, D., Hunt, E.R., 2012. Estimating canopy water content from spectroscopy. Israel J Plant Sci 60:9–23.

Verhoef W., 1984. Light scattering by leaf layers with application to canopy reflectance modeling: The SAIL model. Remote Sensing of Environment, 16(2), 125−141.

Vuolo, F., Atzberger, C., Richter, K., D'Urso, G., Dash, J., 2010. Retrieval of biophysical vegetation products from RapidEye imagery. ISPRS TC VII Symposium – 100 Years ISPRS, vol. 38. ISPRS, Vienna, Austria, pp. 281–286.

Vuolo F., Żółtak M., Pipitone C., Zappa L., Wenng H., Immitzer M., Weiss M., Baret F., Atzberger C., 2016. Data service platform for Sentinel-2 surface reflectance and value-added products: System use and examples. Remote Sens. 2016, 8.

Thorp, K.R., Wang, G., West, A.L., Moran, M.S., Bronson, K.F., White, J.W., Mon, J., 2012. Estimating crop biophysical properties from remote sensing data by inverting linked radiative transfer and ecophysiological models. Publications from USDA-ARS / UNL Faculty, Paper 1173.

Watson, D. J., 1947. Comparative physiological studies in the growth of field crops I. Variation innet assimilation rate and leaf area between species and varieties, and within and between years.*Annals of Botany*, Vol. 11, pp. 41–76.