A HAND-HELD CROP MEASURING DEVICE FOR ESTIMATING HERBAGE BIOMASS AND LAI STATUS IN AN ITALIAN RYEGRASS FIELD

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ABSTRACT: In practical agricultural managements, timely and accurate assessments of plant biophysical parameters such as herbage biomass (BM) and leaf area index (LAI) are required to develop a management strategy especially throughout a growing season. This study investigated the use of a cloud-free hand-held crop measuring device which measures three wavebands (550, 650, and 880 nm) (EBARA Co. Ltd., Japan) as an assessing tool for estimating BM and LAI in an Italian ryegrass (*Lolium multiflorum* Lam.) meadow field (1.8 ha). The data were collected at randomly selected 132 plots for BM and 120 plots for LAI with vegetation sampling through 11 times in two cool growing seasons during October 2010 to March 2011 and December 2011 to March 2012. Eight vegetation indices (VIs) such as normalized difference vegetation index (NDVI) and soil adjustment vegetation index (SAVI) were examined to estimate BM and LAI. The relationship between VIs and parameters were examined using linear regression analyses and significant correlation coefficient (R^2) was observed in most VIs. NDVI showed the highest correlation for both BM (R^2 = 0.77) and LAI (R^2 = 0.81). The robustness of the prediction was examined using cross-year validation. NDVI showed the highest performance for BM (R^2 = 0.77) and SAVI (R^2 = 0.70).

1. INTRODUCTION

Site specific precision agricultural managements can enhance crop production while minimizing potential environmental pollution (Khosla and Shaver, 2001). Essential components of precision agriculture are to obtain spatial information and map factors and spatial and temporal variation (Goel, 2003) that affect productivity. Especially, herbage biomass (BM) and leaf area index (LAI) parameters provide important information that is useful to facilitate the decision process (Asseng et al., 2000). Ground-based multispectral radiometer can measure pasture variability quickly, nondestructively, and inexpensively (Tarr et al., 2005). However, optical sensor based remote sensing technologies have long been hampered by whether condition. To overcome this problem, a hand-held crop measuring device which can measure three wavebands (550nm [green], 650nm [red], and 880 [NIR]) for both upward and downward directions was developed for paddy field by Japanese Bio-oriented Technology Research Advancement Institution. (Horio and Konya, 2007). The photosensors of this device are set up in both upward and downward directions that enable to measure even under unstable weather conditions.

The potentials of the device on grassland were demonstrated by previous studies. To date, only Makino *et al.* (2006) published the report on pasture research using the device and showed that the correlation coefficient (r) between the NIR reflectance obtained from the device and the harvested forage biomass was high (r = 0.7). Recent work by Watanabe *et al.* (Unpublished) tried to estimate herbage biomass and crude protein (CP) concentration using each waveband and vegetation indices in a mixed-sown pasture in Hokkaido, Japan.

In this study, we have attempted to apply the hand-held crop measuring device for estimation of BM and LAI in Italian ryegrass meadow field. The purpose of this study is (i) to demonstrate the potential of hand-held crop growth measuring device for estimation BM and LAI under various weather conditions, (ii) to determine suitable analysis methods and (iii) to demonstrate identifying the spatial and temporal variation of herbage biomass and leaf area index in meadow field and determine suitable spatial resolution in Italian ryegrass (*Lolium multiflorum* Lam.) meadow field.

2. MATERIAL AND METHODS AND EQUATION

2.1 Study Site

The study was conducted in an Italian ryegrass meadow field (1.8 ha) at the Setouchi Field Science Center, Saijo Station (34°23' N, 132°43' E), Hiroshima University (Figure 1). Italian ryegrass is of one of the most important cool season species for temperate grassland agriculture in the world (Barnes *et al.*, 1995), because it regarded as ideal species for use as annual forage grass that establish and grow quickly and provide dense swards of highly nutritious and easily digestible (Yamada *et al.*, 2005). In this site, Italian ryegrass is usually used as a main winter forage crop, with seeding in the autumn season and harvest twice in mid-April and early June (Kawamura *et al.*, 2011). This area is in a temperate zone, with warm, humid summers and cool, dry winter. The annual mean temperature is 10°C; the mean temperature of the coldest and warmest months were , 0°C in January and ; 25.8 °C in August, respectively. The annual precipitation is 1,499 mm in 2011.

Figure 1: Location of the experimental meadow (1.8 ha) and six permanent lines plot (n = 112) for spectral readings.

2.2 Measuring Device

Canopy reflectance was measured by hand-held crop growth measuring device (1.0 kg in weight, 148 [H] × 795 [W] × 146 [D] mm in size, Ebara Corporation, Tokyo, Japan), which was originally developed by the Bio-oriented Technology Research Advancement Institution, Japan (Horio and Konya, 2007). The device consists of sensors, a controller with a monitor operated by eight key buttons, a hand-grip that has a measurement start organizer and internally a battery holder for four AA-cells, a haft part and a marker rod that folds up (Watanabe *et al.*, Unpublished) (Figure 2). The sensor has three silicon photodiode detectors attaching each spectral filter (green, 550 nm [full-width-half-maximum 50 nm]; red, 650 nm [80 nm]; NIR, 880 nm [50 nm]) in the upward and downward directions, respectively. The sensor having both upward and downward directions enables simultaneous measurement of both the intensity of the incident light to a target crop and the reflected light from the crop. Solar diffuser plates are also attached to the top of the upward sensors in order to avoid the effects of changes in the angle of incident light. The effects of outside light conditions on the spectral reflectance of a target crop are diminished and consequently stable reflection measurement become possible even under unstable insolation conditions due to these mechanisms. The spectral reflectance ratio values (r_x) against a standard white plate in each waveband (x = 550, 650, or 880 nm) are calculated by the following equation (Horio and Konya, 2007) :

$$r_x = \frac{I_{dx} - D_{dx}}{I_{ux} - D_{ux}} \times W_x \qquad (1)$$

where d and u mean the directions of the sensors which are downward and upward, respectively, I is the light intensity value in each sensor and D is the offset value that has been predetermined in each sensor and W is the coefficient for the white reference, which was calculated as the reciprocal ratio of the measurement value of the incident / reflected light intensities in each wavelength of the standard white plate (Watanabe *et al.*, Unpublished).

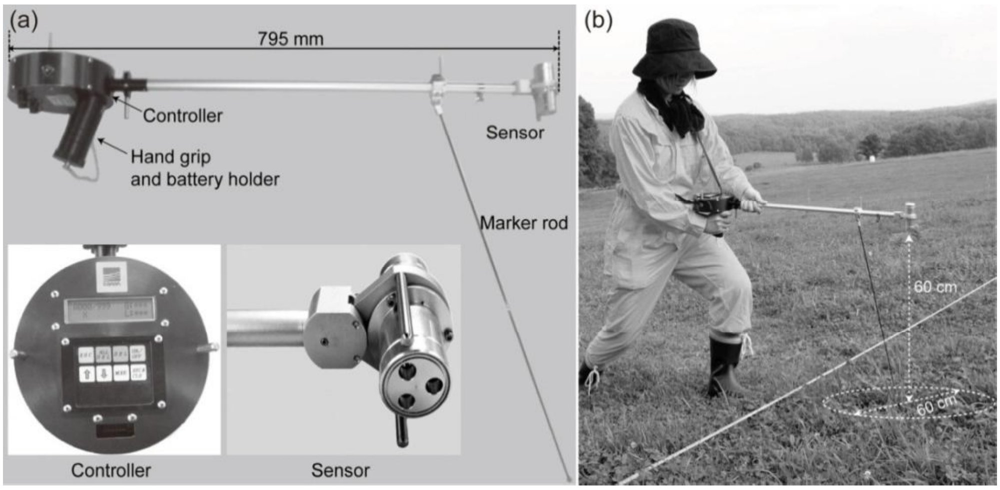

Figure 2: Hand-held crop measuring device (Watanabe *et al.*, Unpublished)

2.3 Measurements

Canopy reflectance spectra were collected 11 times throughout the two growing seasons. In the first season, 6 times of measurements were conducted on 26 November and 23 December in 2010, and 3 February, 3 March, 31 March, and 21 April in 2011 and in the second season, 5 times measurements were also conducted on 13 December in 2011, and 24 February, 8 March, 27 March and 18 April in 2012. Measurements were made on clear sky and cloudy dates between 10:00 and 13:00 hour local time (GMT +09:00).

Reflectance data were collected as 2 types for making calibration model and mapping. For making calibration models, 132 quadrats (0.25 m^2) were randomly selected with vegetation samplings. Also, separate spectral readings were made at totally 112 sites on six permanent lines with every 10 m interval for mapping purpose (Figure 1). The reflectance was measured approximately 60 cm above the canopy at nadir position, producing a view area with a 30 cm diameter at canopy level. In all of the measurements, location data (Universal Transverse Mercator [UTM] zone 53) were recorded using a differentially corrected global positioning system (DGPS) receiver Hemisphere A100 GPS (Hemisphere Co. Ltd., Calgary, Canada) and ArcGIS software version 9.2 (ESRI, Inc., Redlands, CA, USA).

2.4 Regression Analysis

In order to determine the relationships between measured spectral data (R550, R650 and R880) and BM and LAI, linear regression analyses were performed using vegetation indices (VIs). The plant parameters were used in normal and logarithmic (ln) and eight published VIs were used for estimation; ratio vegetation index (RVI) (Jordan, 1969), green/red ratio (Green/Red) (Kanemasu, 1974), Normalized differential vegetation index (NDVI) (Rouse *et al.*, 1973), green NDVI (Gitelson *et al.*, 1996), soil adjusted vegetation index (SAVI) (Huete, 1988), modified SAVI (MSAVI) (Qi *et al.*, 1994), renormalized difference vegetation index (RDVI) (Roujean and Breon, 1995) and modified simple ratio (MSR) (Chen, 1996) (Table 2.2). The performance of the model was evaluated by comparing differences in the coefficient of determination (R^2) and root mean square error (RMSE). RMSE defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{1}^{n}(y_i - \hat{y}_i)^2} \qquad (2)$$

where y_i, $\hat{y}_i$ were measured and predicted values, respectively. The model which has the larger R^2 and smaller the RMSE values were selected to estimate BM and LAI.

To evaluate the performance of robustness for calibration model to estimate BM and LAI parameters which have collected throughout two continuous growing seasons, the model was applied to the other year's data set. Then, this predicted variable was validated using the target season's measured values. All data handling and regression calculations were performed in Matlab software version 7.10 (Mathworks Inc., Sherborn, MA)

Table 1: Vegetation indices (VIs) used in this study to estimate herbage biomass (BM) and leaf area index (LAI)

Index	Formula	Reference
RVI	$\mathrm{RVI} = \frac{\mathrm{NIR}}{\mathrm{RED}}$	Jordan (1969)
Green/Red	$\mathrm{Green/Red} = \frac{\mathrm{GREEN}}{\mathrm{RED}}$	Jordan (1969)Kanemasu (1974)
NDVI	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}$	Rouse *et al.* (1973)
GNDVI	$\mathrm{GNDVI} = \frac{\mathrm{NIR} - \mathrm{GREEN}}{\mathrm{NIR} + \mathrm{GREEN}}$	Gitelson (1996)
SAVI	$\mathrm{SAVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED} + L}(1 + L)$	Huete (1988)
MSAVI	$\mathrm{MSAVI} = \frac{2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - RED)}}{2}$	Qi *et al.* (1994)
RDVI	$\mathrm{RDVI} = \frac{NIR - RED}{\sqrt{NIR + RED}}$	Roujean and Breon (1995)
MSR	$\mathrm{MSR} = \frac{NIR/RED - 1}{\sqrt{NIR/RED + 1}}$	Chen (1996)

2.5 Geostatistical Analysis

To find out the spatial and temporal variability of BM and LAI geostatistical analysis was conducted using canopy reflectance data measured in permanent line plot.. BM and LAI were estimated by using VI which have the highest predictive accuracies among the eight VIs and MLR in Matlab. Geostatistical analysis was performed with “gstat” package version 0.9-40 (Pebesma, 2004) and “automap” package version 1.0-90 (Hiemstra *et al.*, 2009) on “R” statistical software version 2.13.0 (R Development Core Team, 2011). Spatial distribution maps of BM and LAI were generated from the estimated three parameters along with easting (longitude) and northing (latitude).

Semivariance was calculated to determine the spatial dependence of BM and LAI. The semivariance $\gamma\ (h)$ is defined as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N} [z(x_i) - z(x_{i+h})]^2 \qquad (3)$$

where h is the lag distance between N sample pairs, x_i is a location, $z(x_i)$ is the measured value at location x_i, $z(x_i + h)$ is the sample value at point $x_i + h$, and $N(h)$ is a function of the lag distance (Webster, 1985, Crist, 1998)
Among the semivariogram models, which are linear model, shperical model, exponential model, Gaussian model, Matern, M. Stein's parameterization, one of model was selected as the best fit. Linear model is defined as:

$$\gamma(h) = C_0 + C(h/A_0) \qquad (4)$$

spherical model is defined as:

$$\gamma(h) = \begin{cases} C_0 + C[1.5(h/A_0) - 0.5(h/A_0)^3] & (for\ h \le A_0) \\ C_0 + C & (for\ h > A_0) \end{cases} \qquad (5)$$

exponential model is defined as:

$$\gamma(h) = C_0 + C[1 - exp(-h/A_0)] \qquad (6)$$

Gaussian model is defined as:

$$\gamma(h) = C_0 + C\left[1 - exp\left(-h^2/{A_0}^2\right)\right] \qquad (7)$$

and M. Stein's parameterization is defined as:

$$\gamma(h) = C_0 + C\left[1 - exp\left(-h^2/{A_0}^2\right)\right] \qquad (8)$$

where C_0, C and A_0 are the nugget variance, structural variance and range parameter, respectively. $C_0 + C$ is the total variance or sill, and a is the range or correlation length (the lag at which the semivariance achieves a plateau). The k parameter (the ratio of the nugget to the sill, $C_0/(C_0 + C)$) is used to evaluate the amount of randomness of the data at distances smaller than the sampling distance (Cambardella *et al.*, 1994). When $k < 0.25$, the pasture parameter is considered to be spatially dependent or strongly distributed. If k is between 0.25 and 0.75, the pasture parameter is considered to be moderately spatially dependent. When $k > 0.75$, the pasture parameter is considered to have very weak spatial dependence.

The parameters of the selected semivariogram model were used to generate distribution maps of BM and LAI by using an ordinary point kriging method.

3. RESUTLS

3.1 Estimation of BM and LAI

The mean values ± standard deviation for BM and LAI of collected sample (n = 132 for BM, n = 120 for LAI) were 332.91 ± 259.85 (g DM m^{-2}) and 4.27 ± 3.13 (m^2 m^{-2}), respectively (Table 2). The results of regression analyses and cross-year validation between BM and LAI and eight VIs are showed in Table 3. The correlation coefficients between VIs and BM and LAI in natural and logarithmic form were significant at $P < 0.01$except for Green/red ratio index. Except for that, most of VIs showed significant predictive accuracies in the logarithmic form for BM (R^2 = 0.60-0.77) and LAI (R^2 = 0.68-0.81) than normal form. The highest R^2 were generated from NDVI for ln BM (R^2 = 0.77) and ln LAI (R^2 = 0.81). In the result of cross-year validation of each calibration model build using logarithmic form of BM and eight VIs, NDVI (R^2 = 0.70) shows the highest robustness of predictive performance and SAVI (R^2 = 0.67) was ranked as second. On the other hand, for the estimation of LAI, SAVI (R^2 = 0.77) was ranked higher than NDVI (R^2 = 0.76).

Table 2: Range of pasture parameters of the sampling plots.

Parameters	1st growing season			2nd growing season		
	Range	Mean	CV	Range	Mean	CV
BM (g m^{-2})	2.0 - 1067.6	374.64	1.36	15.4 - 1101.4	282.82	1.21
LAI (m^2 m^{-2})	0.04 - 14.83	4.64	1.45	0.30 - 11.93	3.72	1.26

CV, Coefficient of Variation = Mean/SD

Table 3: Correlation coefficient of determination (R^2) and root mean square error (RMSE) between vegetation indices (VIs) and parameters in normal and logarithmic form and cross-year validation.

VIs	Parameters									
	Normal form				Logarithmic form					
	BM		LAI		ln BM			ln LAI		
	R^2	RMSE	R^2	RMSE	R^2	RMSE	Cross-year validation	R^2	RMSE	Cross-year validation
RVI	0.42	197.38	0.48	2.25	0.60	0.75	0.41	0.68	0.61	0.52
Green/Red	0.01 *	257.64	0.05 *	3.04	0.02 *	1.17	0.06	0.03 *	1.06	0.09
NDVI	0.38	203.38	0.42	2.37	**0.77**	**0.57**	**0.70**	**0.81**	**0.47**	0.76
GNDVI	0.32	213.06	0.39	2.43	0.66	0.69	0.53	0.71	0.58	0.61
SAVI	0.37	206.17	0.44	2.33	0.73	0.62	0.67	0.80	0.48	**0.77**
MSAVI	0.4	201.08	0.45	2.32	0.75	0.59	0.66	0.81	0.47	0.75
RDVI	0.38	203.73	0.45	2.31	0.71	0.64	0.62	0.79	0.5	0.73
MSR	0.42	197.15	0.47	2.27	0.68	0.68	0.51	0.74	0.55	0.61

* Represents that significant correlation is not observed ($P > 0.05$).

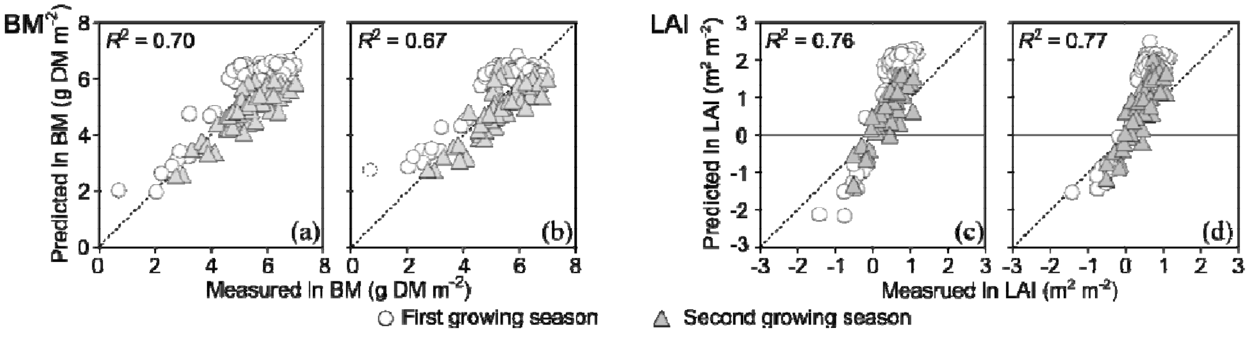

Figure 3: Cross-year validation of the calibration model of BM estimated from NDVI (a) and SAVI (b) and LAI estimated from NDVI (c) and SAVI (d).

3.2 Estimation of Spatial and Temporal Distribution of BM and LAI

Geostatistical analysis was conducted with estimated BM and LAI using NDVI, which showed the highest correlation. The semivariograms of BM and LAI during two continuous growing seasons were well described by the selected semivariogram models with estimated parameters (Figure 4). The figures shows experimental (circle) and modeled (line) semivariograms of pasture parameters using each selected model. The parameter range (a) of the selected semivariograms were 21.32, 14.53,15.97, 18.81, 23.80, 23.22, 25.18, 31.31, 34.86 and 44.10 for BM, 21.26, 14.75, 16.02, 18.88, 26.15, 23.31, 25.08, 31.16, 34.74 and 43.86 for LAI. Second growing season was showed higher range value (a) than first growing season and the range value was increase as growing season goes on in both seasons. Kerry and Oliver (2004) suggest that the sampling intervals should be the half of variogram range value. Considering the results of suitable sampling interval, spatial distribution map of BM and LAI were generated to 5 m grid as a mapping resolution (Figure 5). After generating spatial distribution maps with 5 m grid, the average for predicted BM and LAI was calculated (Figure 6). Second growing season showed lower productivity than first growing season.

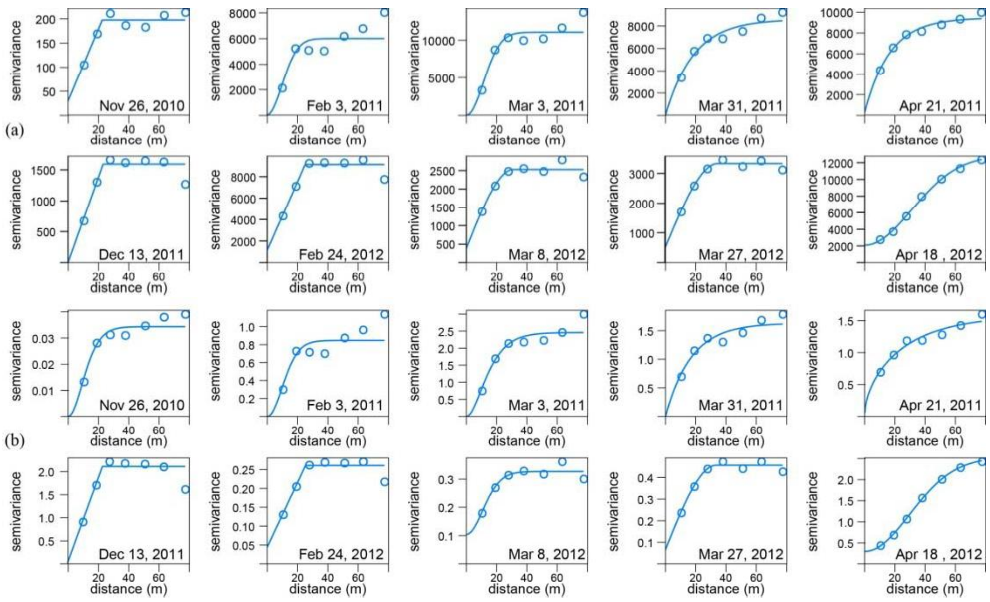

Figure 4: Semivariogram models of herbage biomass (BM) (a) and leaf area index (LAI) (b) estimated from NDVI in two continuous growing season.

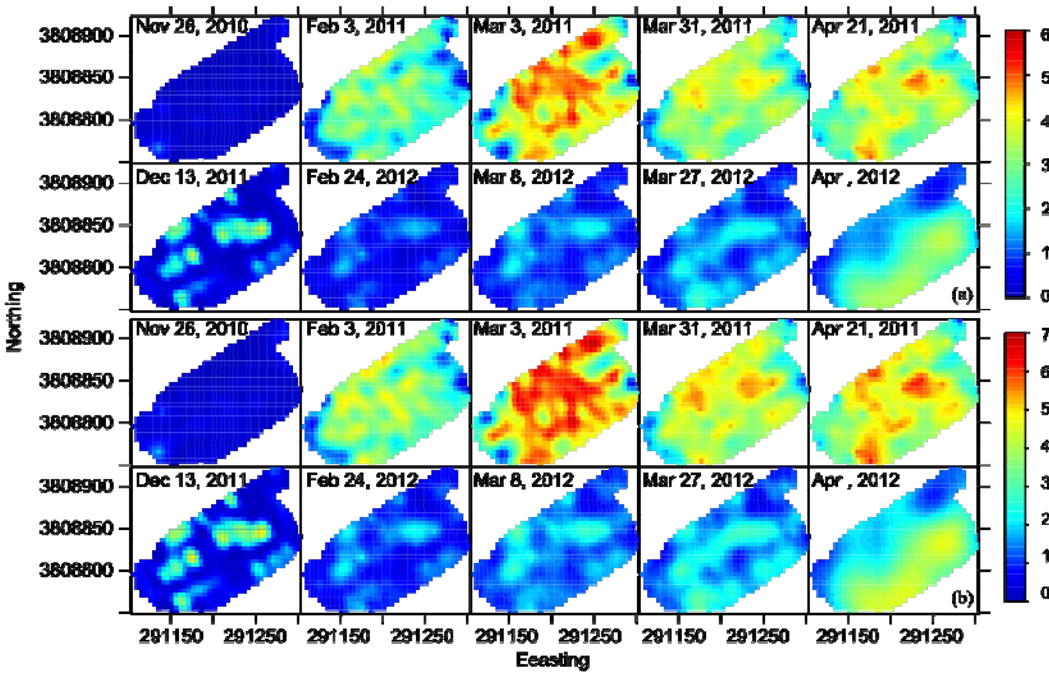

Figure 5: Spatial distribution map of BM (a) and LAI (b) estimated using NDVI.

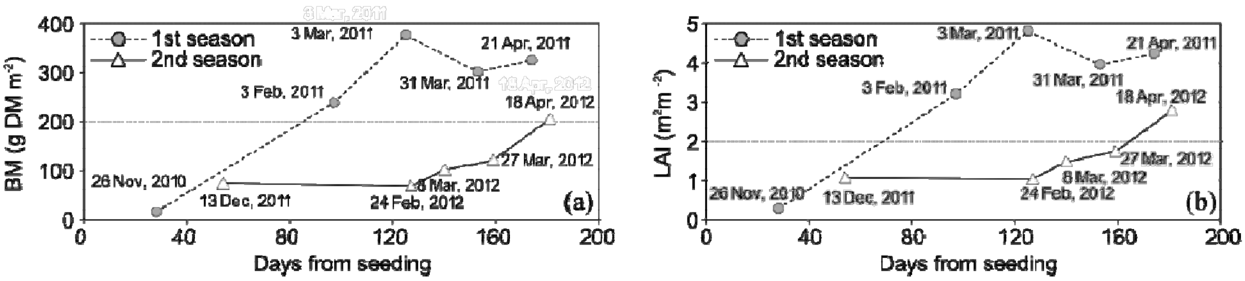

Figure 6: Temporal changes of averaged values of predicted BM(a) and LAI(b) using NDVI in whole field over growing seasons.

4. DISCUSSION

4.1 Suitable VIs to estimate BM and LAI using the hand-held crop measurement

NDVI was the most appropriate VI to estimate BM and LAI in this study. The NDVI has been most widely used vegetation index (Tucker and Sellers, 1986). It is have been known to be well correlated with various biophysical plant parameters including green leaf area and biomass (Sellers, 1985). However, because of the limitation of NDVI which is influenced partial canopy spectra soil background condition, SAVI was developed (Huete, 1988). In this study, though NDVI showed stronger correlation than SAVI in the pooled dataset of two growing seasons, SAVI showed higher performances relatively than NDVI in individual dataset of each measurement. It was considered as that grass coverage in the meadow field changes by the plant growth over growing season from the stage of seeding.

The performances of estimation about both BM and LAI in late growing season were decreased (Figure 7) and approach a saturation level around 600 g m^{-2} for BM and 4 m^2 m^{-2} for LAI (Figure 8). The saturation relationship between biomass and VIs based on the red and NIR waveband such as NDVI and SAVI is a well-known problem that they asymptotically approach a saturation level after a certain biomass density or LAI (Tucker, 1977, Sellers, 1985, Gao *et al.*, 2000). Thus, in practical application for management in late growing season, use of SAVI will be recommended. However, important crop management strategies which affect crop productivity such as fertilizer application are decided in early to mid-growing season. It is expected that the device can be contribute to enhance productivity.

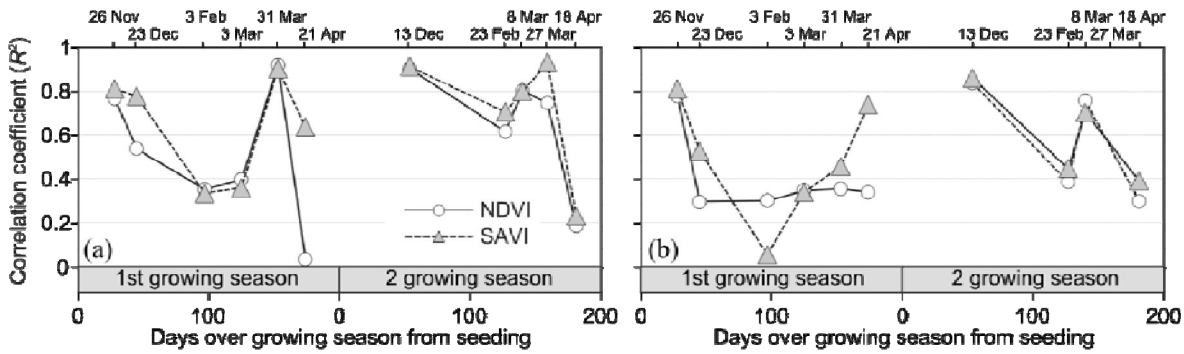

Figure 7: Coefficient of determination (R^2) between Normalized differential vegetation index (NDVI) and soil adjusted vegetation index (SAVI) and BM(a) and LAI(b) over growing seasons.

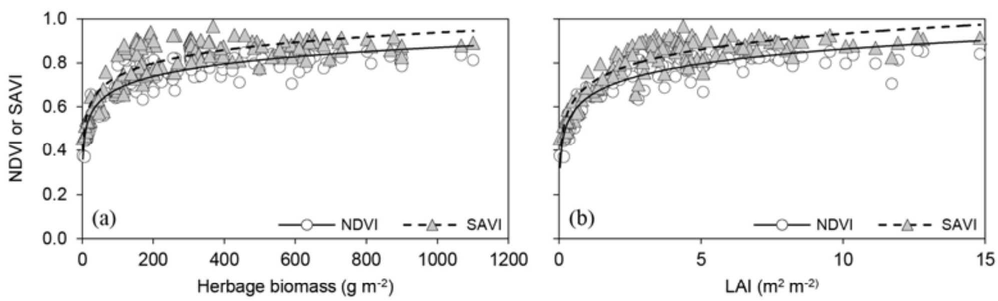

Figure 8: relationship with herbage biomass and normalized differential vegetation index (NDVI) and soil adjusted vegetation index (SAVI) (a) and LAI and NDVI and SAVI (b)

4.2 The Potential as Cloud-Free Tool

The geostatistical analysis through the semivariogram model represented as a plot that gives a picture of the regionalized variable of each point on its neighbor (Curran and Williamson, 1988, Cohen *et al.*, 1990), and it can makes to obtain the practical information regarding spatial variation of vegetation. In this research, semivariogram models were well described the change of spatial and temporal distribution of BM and LAI. The parameters of semivariogram can provide practical information for livestock managers for determining optimal sampling size for monitoring and optimal grid size for mapping for site-specific management of Italian ryegrass meadow field. Furthermore, spatial distribution map with a grid cell sampling method would support the information to be used in further analyses within a geographic information system with regard to environmental factors, such as soil fertility, grazing intensity, etc. (Kawamura *et al.*, 2005). In the measurement on 3 March in 2011, BM and LAI were higher than later measurements (Figure 6). It seems to be overestimated due to the weather condition which was snowy. It is considered as the device is unstable in rainy or snowy day though showed the potential as cloud-free tool.

4.3 The Potential as Real Time monitoring for Suitable Managements

The device could detect real-time temporal changes during growing seasons. Especially, BM and LAI which are strongly related with crop productivity were showed significant differences with 2 continuous growing seasons. Predicted BM (205.33 g DM m^{-2}, 181 days from seeding) and LAI (2.78 m^2 m^{-2}, 181 days from seeding) of second growing season were considerably lower than first growing season for both BM (325.51 g DM m^{-2}, 181 days from seeding) and LAI (4.23 m^2 m^{-2}, 181 days from seeding). Harvested yields were also different in first season (980.12 g DM m^{-2}) and second season (654.54 g DM m^{-2}). As for the difference of the yields, following factors were considered to be important. Naturally, weather conditions were different between the two years. Besides, seeded varieties were different, which was "Inazuma" for first season and "Ace" for second season. Fertilizer applications were also different between the two years.

5. CONCLUSIONS

The potentials of hand-held crop measuring device as a tool to estimate BM and LAI were demonstrated on grassland, particularly in Italian ryegrass field. The device has the abilities to provide the information of present status timely for making management decision. Making calibration model using NDVI was the most appropriate to assess current status of Italian ryegrass field. Also, the device was feasible under cloudy weather condition while it is not allowed to measure the canopy reflectance in snowy or rainy days.

Suitable interval for canopy reflectance measurement of the device was estimated to be approximately 7 m for BM and LAI. However, the homogeneity was increased as growing season goes on. Therefore, the suitable measurement intervals need to be considered by the stage of growing season for effective field managements.

To estimate spatial and temporal variations of BM and LAI in Italian ryegrass meadow field, a hand-held crop measuring device may thus be an easy and comparatively cloud-free method. In the future study, not only the feasibilities of estimation in other pasture nutrient and mineral parameters but also soil status are needed to demonstrate. This study could estimate the different result in the herbage biomass quantity of two growing season. It is need to comparative analysis between two growing seasons considering other external factors such as weather condition, soil status, fertilization, agronomy and other managements.

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