A HAND-HELD CROP MEASURING DEVICE FOR ASSESSING SPATIAL VARIABILITY OF HERBAGE BIOMASS AND LAI IN AN ITALIAN RYEGRASS FIELD

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ABSTRACT: Understanding spatial and temporal distribution of herbage biomass (BM) and leaf area index (LAI) are important in refining agricultural management practice. This study investigated the use of a hand-held crop measuring device (EBARA Co. Ltd., Japan), which measures three wavebands (550, 650, and 880 nm), for estimating spatial and temporal variation of BM and LAI in an Italian ryegrass (*Lolium multiflorum* Lam.) meadow (1.8 ha). The field experiments were made at five times in a single growing season during October 2010 to April 2011. Using the device, canopy reflectance data was collected at randomly selected 72 plots with vegetation sampling, and BM and LAI were measured for calibration. For mapping purpose, separate spectral readings at 112 plots were conducted on six permanent lines with every 10 m interval in each time. Regression analysis showed that the normalized difference vegetation index (NDVI) was strongly correlated with BM (R^2 = 0.73) and LAI (R^2 = 0.87). The result of geostatistical analysis using semivariogram model represented that optimal sampling intervals were ranging from 8.3 to 11.1 m about BM and from 5.9 to 11.2 m about LAI over the sampling dates. These results suggested that suitable spatial resolutions should be less than 8 m for BM estimation and 6 m for LAI estimation. For estimation and mapping of BM and LAI in Italian ryegrassa, hand-held crop measuring device may thus be an easy and comparatively cloud-free method.

1. INTRODUCTION

Recently developed site-specific agricultural management systems, also known as precision agriculture, provide a method that involves cost reduction, optimization of crop yield, and environmental protection (Bouma 1997). Essential components of precision agriculture are to obtain spatial information on and map factors that affect productivity, and spatial and temporal variation (Goel et al., 2003). The application of remote sensing techniques in crop management systems has been increased steadily over the last few years (Perbandt et al., 2011). Earlier studies indicated that pasture variability measurements using a ground-based multispectral data can be performed quickly, nondestructively, and inexpensively (Tarr et al., 2005). However, optical remote sensing data are strongly affected by atmospheric condition. To overcome this problem, a hand-held crop measuring device was developed for paddy field rice by Japanese Bio-oriented Technology Research Advancement Institution. The device, which has sensor both upward and downward directions, can simultaneously monitor a solar radiation and canopy reflectance, then provides internally atmospheric corrected canopy reflectance data. According to Watanabe et al. (2010), this device can be applied for the monitoring of herbage biomass (BM) in a mixed-sown grazed pasture.

Italian ryegrass (*Lolium multiflorum* Lam.) is one of the most important 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). Understanding spatial and temporal distribution of Italian ryegrass meadow parameters is important for the management practice of Italian ryegrass meadow. Especially, herbage BM and leaf area index (LAI) parameters provide important information that is useful to facilitate the decision process (Asseng et al., 2000).

The purpose of this study is (i) to estimate BM and LAI of Italian ryegrass using the hand-held crop measuring device, and (ii) to determine their spatial and temporal pattern within the Italian ryegrass field during a growing season using geostatistical analysis.

2. MATERIAL AND METHODS

2.1 Experimental Site

This research was conducted in an Italian ryegrass meadow (1.8 ha) at the Setouchi Field Science Center, Saijo Station (34°23′N, 132°43′E), Hiroshima University (Figure 1). 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.* , unpublished). This area is in a temperate zone, with warm, humid summers and cool, dry winter. The annual mean temperature is 13.5 °C, and the annual precipitation is 1445.9 mm.

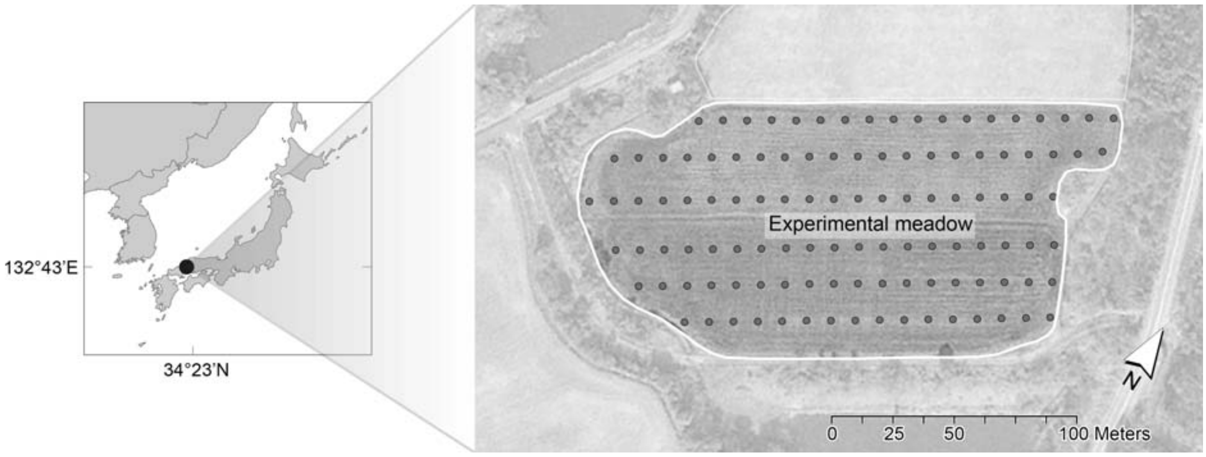

Figure 1 Location of the experimental meadow (1.8 ha) and sampling point (n = 112) for spectral reading.

2.2 Measurements

Canopy reflectance measurements were collected five times on 26 November and 23 December in 2010, and 3 February, 31 March, and 21 April in 2011 throughout the growing season.A hand-held crop measuring device (EBARA Co. Ltd., Japan) was used and it measured three wavebands (550 nm (green band), 650 nm (red band), and 880 nm (near infrared (NIR) band)). Measurements were conducted during on clear days between 10:00 and 13:00 hour local time (GMT +9). Reflectance data were collected from randomly selected 72 quadrats (0.05m^2) with vegetation sampling. 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. After reflectance measurements, all vegetation was clipped to ground level. The forage samples were transported to a laboratory and the surface area of the leaf samples was determined by the use of a leaf area meter (Automatic Area meter, Hayshi Denco Ltd., Japan) and LAI (m^2 m^{-2}) was calculated. Subsequently, all materials were dried at 65 °C for 48 h in a forced-air oven to determine total dry matter (g m^{-2}) to use for the determination of BM.

For mapping purpose, separate spectral readings were made on six permanent lines with every 10 m interval in each time (Figure1). Spectral data were collected from 112 quadrats with location data (Universal Transverse Mercator [UTM] zone 54) using a real-time kinematic global positioning system receiver ((Leica SR530 + AT502 antenna system; Leica Geo-systems Inc., GA, USA)) and ArcGIS software version 9.2 (ESRI, Inc., Redlands, CA, USA).

2.3 Regression Analysis

In order to determine the relationships between measured spectral data and BM and LAI, regression analyses were performed using the normalized difference vegetation index [NDVI = (R_{NIR} - R_R)/(R_{NIR} + R_R)] and green normalized difference vegetation index [Green NDVI =(R_{NIR} – R_G)/(R_{NIR} + R_G)]. The performance of the model was evaluated by comparing the differences in the coefficient of determination (R^2) and root mean square error RMSE. RMSE defined as:

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

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

2.4 Geostatistical Analysis

Geostatistical analysis was conducted about the predicted GBM and LAI from collected canopy reflectance to identify spatial and temporal variability. 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).

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

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

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).

Subsequently, the exponential variogram model was applied. Exponential variogram model is defined as:

$$\gamma(h) = c_0 + c[1 - \exp(-h/a)] \quad (3)$$

where c_0 is the initial or nugget variance, c is the structural variance or the variance due to spatial dependence across lag distances (the semivariance value of the plateau), $c_0 + c$ 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.

Finally, 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. RESULTS

3.1 BM and LAI Estimation

Table 1 showed the result of regression analysis with NDVI and Green NDVI about BM and LAI. Applying regression analysis, exponential-type were better fitted than linear-type about NDVI with BM (Linear, Lin; $R^2 = 0.35$, Exponential, Exp; R^2 = 082.), NDVI with LAI (Lin; $R^2 = 0.40$, Exp; $R^2 = 0.87$), Green NDVI with BM (Lin; $R^2 = 0.30$, Exp; $R^2 = 0.73$) and Green NDVI with BM (Lin; $R^2 = 0.41$, Exp; $R^2 = 0.80$). In case of exponential-type, NDVI had a better relationship with BM and LAI than Green NDVI (Figure 2). Thus, NDVI with exponential-type was used to estimate BM and LAI from the field measured canopy reflectance data.

Table 1 Result of regression analysis with normalized difference vegetation index (NDVI) and green normalized difference vegetation index (Green NDVI) about BM and LAI

Grass Parameters	Vegetation Index	Function type	a	b	R^2	RMSE
BM (g m^{-2})	NDVI	Linear	1282.80	606.91	0.35	219.44
		Exponential	0.12	9.78	0.82	218.30
	Green NDVI	Linear	993.84	403.80	0.30	228.84
		Exponential	0.48	7.83	0.73	284.85
LAI (m^2 m^{-2})	NDVI	Linear	15.87	7.50	0.40	2.47
		Exponential	0.00	8.53	0.87	2.30
	Green NDVI	Linear	13.62	6.03	0.41	2.45
		Exponential	0.01	6.91	0.80	2.71

Linear-type, Y = a + bX; Exponential-type, Y = a*Exp (bX); Root mean square error, RMSE.

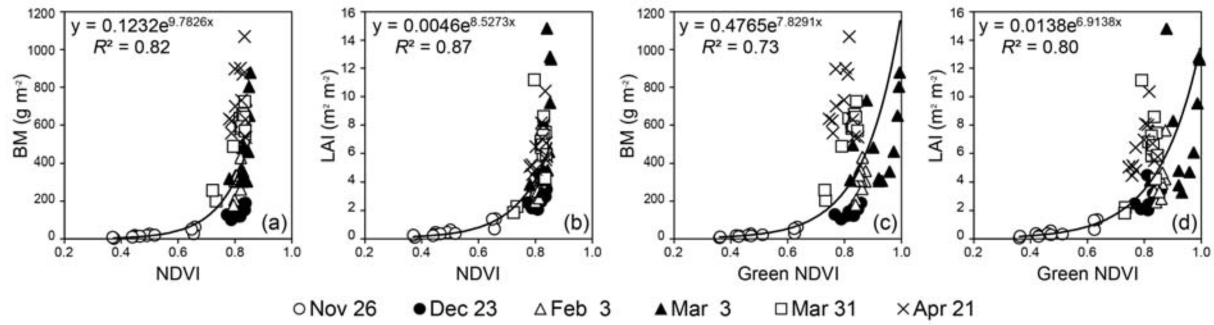

Figure 2 Relationship of NDVI with BM (a) and LAI (b), Green NDVI with BM (c) and LAI (d) form vegetation samples (n = 72).

3.2 Estimating Spatial and Temporal Variability

The semivariograms of BM and LAI during October 2010 to April 2011 in a single growing season were well described by the exponential models (Figure 3) with estimated parameters (Table 2). Parameter k of BM and LAI were almost closed to zero except 3 Feb for BM (k = 0.28; moderately spatially dependent). Thus, the semivariogram models of BM and LAI showed almost the same results except 3 Feb for BM, with k values within the range indicating spatially dependent or strongly distributed ($k < 0.25$).

The parameter range (a) of the exponential semivariograms were 13.2, 17.2 15.4, 18.9 and 16.6 for BM and 11.7, 13.0, 15.0 18.8 and 16.3 for LAI on 26 November, 3 February, 3 March, 31 March and 21 April, respectively. The range parameter of the semivariograms gives the average size of the patches when the distribution patterns of pasture parameters shows strong or moderate spatial dependency (López-Granados et al. 2004). Therefore, the estimated range value in semivariograms indicated that BM values influenced by neighboring BM values up to 13.2 and 18.9 m away, respectively, and LAI were influenced by neighboring LAI values up to about 11.7 and 18.8 m away. The range value of LAI was gradually increased from November to March and decreased on April, indicating that LAI values became less influenced by neighboring values according to the plant growth until March, and became more influenced by neighboring values on April. It means that the spatial distribution patterns of LAI became homogeneous until March, and became heterogeneous on April. In case of BM, range value on February showed higher value than March. Except the data on February, the change of the range value was similar with the change of range value of LAI. About whole data collection season, range values of LAI were smaller than those BM, indicating that the spatial distribution patterns of LAI were more heterogeneous than BM.

Kerry and Oliver (2004) suggest that the sampling intervals should be the half of variogram range value. Thus, optimal sampling intervals were ranged from 8.3 to 11.1 m about BM and from 5.9 to 9.4 m about LAI. The results indicated that suitable sampling interval should be less than approximately 8 m for BM estimation and 6 m for LAI estimation in Italian ryegrass meadow. From the results of suitable sampling interval, we selected 5 m grid as a mapping resolution, and spatial distribution map of BM and LAI were generated based on 5 m grid from November of 2010 to April of 2011 (Figure 4). After generating spatial distribution maps with 5 m grid, the average for predicted BM and LAI was calculated. The average of BM were 17.8, 175.5, 257.4, 213.2 and 226.5 (g m^{-2}), and the average of LAI were 0.3, 4.2, 6.7, 5.3 and 5.7 (m^2 m^{-2}) on 26 November, 3 February, 3 March, 31 March and 21 April, respectively.

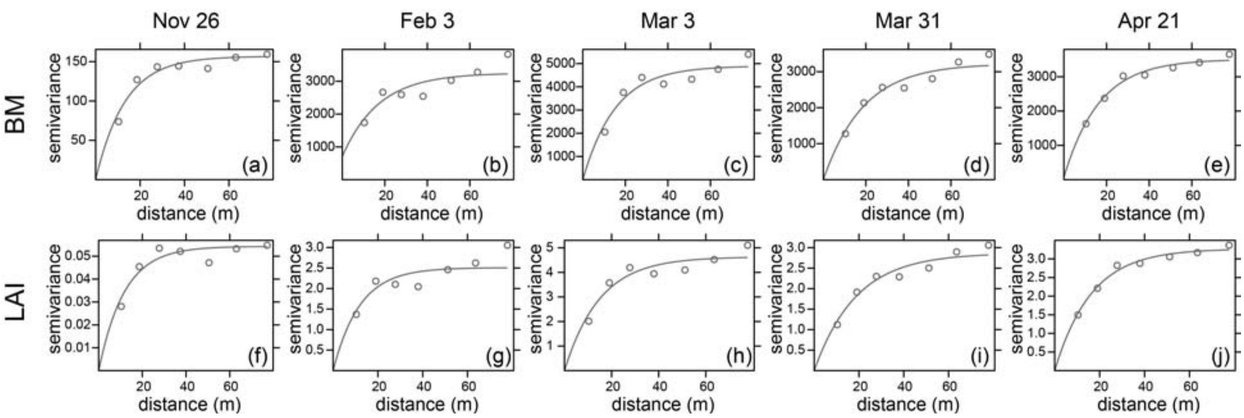

Figure 3 Exponential Semivariograms (circles, measured values; line, estimated values) about BM (a, b, c, d, e) and LAI (f, g, h, i, j) from November 2010 to April 2011.

Table 2 Exponential semivariogram model parameters about BM and LAI

Semivariogram model parameter	BM Nov 26	BM Feb 3	BM Mar 3	BM Mar 31	BM Apr 21	LAI Nov 26	LAI Feb 3	LAI Mar 3	LAI Mar 31	LAI Apr 21
Nugget (c_0)	0.0	709.6	0.0	0.0	68.3	0.0	0.0	0.0	0.0	0.0
Sill (c_0+c)	156	2543	4898	3224	3441	0.05	2.40	4.63	2.87	3.27
k (c_0/(c_0+c))	0.00	0.28	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
Range (a)	13.2	17.2	15.4	18.9	16.6	11.7	13.0	15.0	18.8	16.3
Optimal grid size	6.6	8.6	7.7	9.4	8.3	5.9	6.5	7.5	9.4	8.11

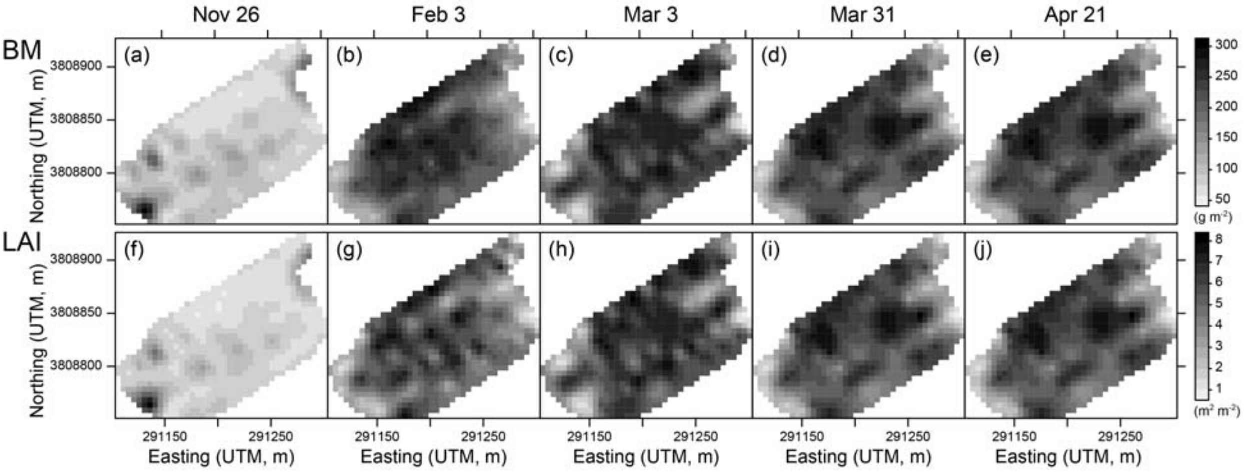

Figure 4 Spatial distribution map of BM (a, b, c, d, e) and LAI (f, g, h, i, j) with 5m grid from November 2010 to April 2011.

4. DISCUSSION

This study demonstrated the potential of a hand-held crop measuring device for estimating and mapping BM and LAI in Italian ryegrass meadow field. Regression analysis showed that both BM and LAI results were better fitted with the exponential-type compared to the linear-type, and NDVI was strongly correlated with BM (R^2 = 0.73) and LAI (R^2 = 0.87). The NDVI has been most widely used vegetation index in vegetation studies (Townshend *et al*., 1994; Tucker and Sellers, 1986). However, NDVI is sensitive to optical properties of soil background (Baret and Guyet, 1991). Gitelson *et al*. (1996) developed a Green NDVI. They found that the Green NDVI to be sensitive to a much wider range of chlorophyll concentration than the original NDVI. However, NDVI with exponential-type was more sensitive than Green NDVI with exponential-type for estimating BM and LAI using a hand-held crop measuring device in Italian ryegrass meadow field.

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 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 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). 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.

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