HERBAGE BIOMASS AND QUALITY STATUS ASSESSMENT IN A MIXED SOWN PASTURE FROM AIRBORNE BASED HYPERSPECTRAL IMAGING

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ABSTRACT: Aerial hyperspectral imaging is one of the potential tools for the site specific agriculture. This study investigates the use of airborne based hyperspectral sensor, the Compact Airborne Spectrographic Imager 3 (CASI-3) data acquired on July 24, 2007, for estimating spatial distributions of green herbage biomass (GBM), nitrogen (N) and neutral detergent fiber (NDF) concentrations comparing the predictive accuracy with in field hyperspectral measurements in a pasture at Hokkaido, Japan. Canopy spectral measurements were made in the field at 42 plots using an ASD FieldSpec FR Pro spectroradiometer, along with concomitant *in situ* measurements of GBM and concentrations of N and NDF. Three types of partial least squares (PLS) regressions, full-spectrum PLS (FS-PLS), iterative step elimination PLS (ISE-PLS) and genetic algorithm based PLS (GA-PLS), were performed using canopy reflectance data of CASI-3 and ASD, and simulated CASI-3 spectra from ASD (ASD_{CASI}) to predict GBM and concentrations of N and NDF. Among the PLS regressions, GA-PLS showed the best R^2 and lowest RMSECV values in all data set (ASD, CASI-3 and ASD_{CASI}) to predict GBM (R^2 = 0.69-0.86, RMSECV = 48.70-72.68), N (R^2 = 0.61-0.75, RMSECV = 0.25-0.31) and NDF (R^2 = 0.50-0.73, RMSECV = 2.34-3.28). Applying the GA-PLS models on the CASI image, spatial distribution maps of forage GBM and concentrations of N and NDF of herbage were generated.

1. INTRODUCTION

Recent site specific management on grazing system requires data on resource status at a very fine, within-paddock scale which is impractical to collect by traditional method. Increasingly, very fine spatial and spectral resolutions airborne hyperspectral imaging systems are providing new opportunities for investigating and quantifying the herbage mass and forage quality. While aerial photography has traditionally been used for the purpose, hyperspectral sensors on board aircraft, such as the Compact Airborne Spectrographic Imager (CASI) and the Airborne Visible Infra-Red Imaging Spectrometer (AVIRIS), are now being exploited.

Hyperspectral sensors provide a contiguous spectrum defined by a large number of spectral bands, typically measured across the optical wavelengths regions (350–2500 nm). Remotely sensed hyperspectral reflectance signature from plant leaves and/or canopies contain a wide range of biophysical and biochemical information (Kokaly and Clark 1999). On the ground level, field hyperspectral measurements have been widely applied for estimating herbage mass and forage quality such as nitrogen (N), crude protein (CP), neutral detergent fiber (NDF) and acid detergent fiber (ADF) contents (Fava *et al*. 2009; Kawamura et al. 2008; Kawamura *et al*. 2010; Mutanga *et al*. 2004; Starks *et al*. 2006; Zhao *et al*. 2007). Recently, some airborne systems such as CASI and AVIRIS are being employed for larger scale pasture assessment purpose (Beeri *et al*. 2007; Numata *et al*. 2007). Major advantage of the use of airborne based hyperspectral imaging is that improved spectral dimensionality enhances quantification of pasture mass and quality status as a map within-paddock scale.

Predicting herbage mass and forage quality status with imaging spectrometry is a complex undertaking, since plant reflectance is strongly influenced by multiple, overlapping absorption features (Curran *et al*. 1992; Ferwerda *et al*. 2006). Such relationship between spectral measurements and biochemical grassland parameters can be described by both physical and statistical approaches. Thus, physically-based methods often use the radiative transfer models, such as the PROSPECT+SAIL model (Jacquemoud 1993), describing the interaction of radiation with the plant canopy, based on physical principles. On the other hand, statistical methods are based on regression models using either the original reflectance data or spectral indices. Several studies applied stepwise multiple linear regressions (MLR), which use several spectral wavebands to estimate herbage mass and forage quality (Zhao *et al*. 2007). However, the drawbacks of extensive spectral overlap of individual biochemical properties, and multi-collinearity problems are well known. This usually occurs when the number of observations is smaller than the number of wavebands used in the analysis (Curran 1989). In contrast, the partial least squares (PLS) regression has been recommended as an alternative approach to MLR to broaden the information contained in each model and thereby avoid over-fitting.

The purpose of this study was to evaluate the potential and applicability of CASI-3 airborne remote sensing for estimating herbage mass and forage quality in a grazed mixed pasture, comparing with a ground-based hyperspectral remote sensing. The forage quality in this study included N and NDF concentrations of herbage, which were selected as two of major determinants for forage quality (Vallentine 1990). In this study, we also investigated the performance of waveband selection with PLS regression in predicting forage GBM, and N and NDF concentrations of herbage. To date, several waveband selection methods have been developed, such as iterative stepwise elimination PLS (ISE-PLS) (Boggia *et al*. 1997), genetic algorithm PLS (GA-PLS) (Leardi *et al*. 1992). Recent literatures indicated that waveband selection refine the predictive accuracy of the PLS model by optimizing important wavebands both in the laboratory NIRS (Jiang *et al*. 2002) and in the field hyperspectral measurements (Bolster *et al*. 1996; Kawamura *et al*. 2008). In this study, the predictive accuracy of GA-PLS was compared with FS-PLS and ISE-PLS, using the CASI-3 aerial imaging data and ground based canopy reflectance data. Finally, applying the regression model on the CASI-3 image, the spatial distribution maps of GBM, N, and NDF concentrations were created.

2. MATERIALS AND METHODS

2.1. Experimental paddock

The study was conducted in a mixed sown pasture paddock in the NARO Hokkaido Agricultural Research Center, located at 42°59'N, 141°24'E (See Figure 3d). This area is in a snowy cold region with annual snowfall of 5 m. The annual mean temperature is 7.1°C and the annual precipitation is 960 mm. The experimental paddock is consisted of a flat section (Subunit 1, 3.1 ha) and two slope sections (Subunit 2, 2.6 ha; Subunit 3, 2.8 ha). The average slopes of subunits 1, 2, and 3 are 2.1°, 9.0°, and 8.2°, respectively. Subunit 3 includes an area of shelter woods (0.6 ha), dominantly *Betula platyphylla* var. japonica and *Quercus* spp., with a canopy height of 20–30 m. Approximately 35 years ago, the paddock was plowed and seeded in Orchard grass (*Dactylis glomerata* L.), Kentucky bluegrass (*Poa pratensis* L.), meadow fescue (*Festuca pratensis* Huds.), white clover (*Trifolium repens* L.) and perennial ryegrass (*Lolium perenne* L.). Then, in Subunit 1 only, over-seeding of perennial ryegrass was carried out with fertilizer in 2002. Moreover, the north part (0.5 ha) of Subunit 1 was reestablished by sowing perennial ryegrass and Italian ryegrass (*Lolium multiflorum* Lam.) with fertilizer in 2005. At the time of field experiments, perennial ryegrass, orchard grass, and white clover are dominant (Watanabe *et al*. 2004). Here, about ten Japanese Black cows (*Bos taurus* L.) and their calves were stocked during the growing season from early of May to late of October (1.32 head ha^{-1}). They were able to move freely among the three subunits.

2.2. CASI-3 image data acquisition and processing

CASI-3 hyperspectral imaging data was acquired on July 24, 2007 by Nakanihon Air Service Co. Ltd, Japan. The CASI-3 position and orientation system (POS) data was acquired to compensate for aircraft position and movement. The 1-m spatial resolution data were acquired at a flying height of approximately 500 m and in 34 wavelength regions (12-bit) covering the visible to NIR (410–1070 nm wavelength) components of the electromagnetic spectrum.

The spectral radiance was converted to reflectance using empirical line method using ENVI 4.7 software (Exelis Visual Information Solutions). During the flight observation, six 0.9 m × 1.8 m black and white targets were placed in an out of the target paddock, measuring target reflectance with an ASD Field spectrometer (FieldSpec Pro FR; Analytical Spectral Devices Inc., Boulder, CO, USA) calibrated using a spectralon (Labsphere, Inc., Sutton, NH, USA) reference panel. The ASD FieldSpec measures spectral reflectance in the 350–2500 nm wavelength range.

The spectroradiometer has a spectral sampling of 1.4 nm in the 350–1000 nm range, and 2 nm in the 1000–2500 nm range. The spectral resolution is 3 nm in the 350–1000 m range, and 10 nm in the 1000–2500 nm range, which were calculated as 1 nm resolution wavelength for the output data using software (RS2 for Windows®; ASD, Boulder, CO, USA).

2.3. Field hyperspectral measurements and plant data collection

On the same date with CASI-3 aerial observation, field hyperspectral measurements and plant samplings were made at 42 plots within the paddock, which were selected to cover the apparent maximum range in forage mass and quality in the paddock. The location of each plot was measured using a Leica SR530 real-time kinematic (RTK) GPS system. Earlier studies have shown that in relatively open areas the horizontal and vertical accuracy obtained for the RTK GPS measurements are <15 cm and 20 cm, respectively.

Canopy reflectance measurements were performed between 10:00 a.m. and 14:30 p.m. local time (GMT+9). The sensor head was held approximately 50 cm above the canopy at the nadir position. The radiometer had a 25° field-of-view (FOV), producing a view area with a 22 cm diameter at the canopy level. Plant heights were 5–50 cm; consequently, the view area at ground level was between 24 and 44 cm diameter. A spectralon reference panel (white reference) was used to optimize the ASD instrument prior to taking three canopy reflectance measurements at each plot. From the full-spectrum region of ASD FieldSpec data (350-2500 nm), a total of 671 spectral bands between 400 nm and 1070 nm were used for the analysis as similar spectral regions of CASI-3. In addition, to simulate the CASI-3 short-band, spectral resampling from ASD original reflectance spectra (1 nm spectra) to simulated CASI-3 sensor (ASD_{CASI}) was also performed using Gaussian response function based on the center and FWHM.

After spectral readings, all vegetation was clipped within each plot using a 0.09 m^2 (30 cm × 30 cm) quadrat. The forage samples were manually separated into white clover, grasses, weed and dead material (which included litter) and dried in a forced air oven at 70ºC for 48 h to determine dry matter (DM) of biomass (g m^{-2}). The GBM, which included white clover, grasses and weeds, was used in this study.

Chemical analyses were carried out at the Federation of Tokachi Agricultural Cooperative Association Agricultural Product Chemical Research Laboratory. The N concentration was measured using Kjeldahl method (AOAC 1995). NDF concentration was determined using neutral detergent extractions according to (Goering and Van Soest 1970).

2.4. Statistical analyses

The statistical analyses included descriptive and correlation analyses among the pasture parameters, and PLS regression analyses to estimate GBM, N, and NDF concentrations using PLS_Toolbox version 5.5 (Eigenvector Research, Inc., Manson, WA) in Matlab software version 7.7 (Mathworks Inc., Sherborn, MA).

PLS regressions (FS-PLS, ISE-PLS, and GA-PLS) were performed using original canopy reflectance data of CASI-3 and ASD, and simulated CASI-3 spectra from ASD (ASD_{CASI}) to predict GBM and forage quality parameters (N and NDF concentrations). The PLS regression equations are simply described as

$$y = b_1 x_1 + b_2 x_2 \ldots b_v x_v + \varepsilon \qquad (1)$$

where y is a vector with the measured pasture parameters of interest, x is a matrix of reflectance values for spectral band 1 to v, ε is the error vector, and b is the matrix of weighted coefficients for PLS. A large absolute value of the coefficients indicates an important x variable, which is identified as an informative waveband. In the PLS regression, the b matrix is calculated directly from the PLS loadings corresponding to the model with the optimum number of PLS factors or latent variables. In the present study, the minimum value of the root means squared error (RMSECV) from leave-one-out cross-validation was used to select the optimal number of latent variables (NLV) to be included in the regression models.

ISE-PLS is a model-wise elimination technique, developed by Boggia *et al*. (1997), which is based on the importance of the predictors (z_v), defined as:

$$z_v = \frac{|b_v| s_v}{\sum_{v=1}^{V} |b_v| s_v} \qquad (2)$$

where s_v is the standard deviation of the waveband *v*. First, the PLS regression model is developed using all available wavebands. Then, the useless wavebands are eliminated on the basis of the value of predictor z_v in the regression model. In each elimination cycle, the predictor with the minimum importance is eliminated, and the model is computed again using the remaining predictors (wavebands). The final model is that with the maximum predictive ability, as defined by minimum value of RMSECV.

Genetic algorithm (GA) is an efficient numerical optimization method based on genetic principles and natural selection (Leardi *et al*. 1992). GA-PLS is the application of GA in selecting variables for a PLS model. Because of the ability of GA to simulate a natural evolution of an individual, GA is well suitable for solving variable subset selection problems (Ding *et al*. 1998). However, it is well known that the major risk associated with using GA-PLS is over-fitting, because of the large number of variables (wavebands), used in NIRS and hyperspectral data sets. To minimize this risk, our previous study (Kawamura *et al*. 2010), on the ground hyperspectral data analyses, used Leardi (2000) developed GA program. The present study also used same GA program and parameters. For more details of GA-PLS and the parameter setting can be found in Kawamura *et al.* (2010).

The accuracy of the calibration models of the FS-PLS, ISE-PLS and GA-PLS using CASI-3, ASD and ASD_{CASI} were evaluated by the cross-validated coefficient of determination (R^2) and the root mean squared error (RMSECV) values using leave-one-out cross validation.

Spatial distribution maps of GBM, concentrations of N, and NDF were generated by applying the models, which showed the best performance in predictive accuracy on the CASI-3 imagery data, In this step, some areas of shelter wood, tree canopy covered inside the paddock, and their shadows were masked and omitted to this analysis (see Figure 4).

3. RESULTS AND DISCUSSION

3.1. Forage characteristics

Table 1 shows results of the descriptive analysis (min, max, mean, standard deviation [SD], and coefficient of variation [CV]) for forage GBM and concentrations of N and NDF in the 43 samples, with the correlation coefficient (r) among these parameters. Field samples gave a wide range in GBM (CV = 46.0%) and low CV in NDF (CV = 8.4%). The averaged values of GBM, N and NDF concentrations were 284.7 g m^{-2}, 1.8%, and 52.6%, respectively. At the time of our field experiments, grasses are nearly reached peak growth stage with 29.4 cm surface sward height (Kawamura *et al*. 2011). GBM had a high positive correlation with NDF concentration (r = 0.69, P < 0.001), and a negative correlation with N concentration (r = –0.44, P < 0.01). Strong negative correlation was also shown between NDF and N concentrations (r = –0.70, P < 0.001).

Table 1: Descriptive statistics of green forage biomass (GBM) and concentrations of nitrogen (N) and neutral detergent fiber (NDF) in the experimental paddock, with correlation coefficient (r) among the parameters.

Pasture parameters†	Mean	Min	Max	SD	CV	Correlation among paramet		
						GBM	N	NDF
Total green biomass (GBM, gDM m^{-2})	284.7	93.6	629.3	131.0	46.0	1		
Nitrogen (N, %DM)	1.8	1.1	3.2	0.5	27.8	-0.44^{**}	1	
Neutral detergent fiber (NDF, %DM)	52.6	45.5	61.2	4.4	8.4	0.69^{***}	-0.70^{***}	1

†Biomass (BM) data are expressed on a dry matter basis.

** Significant at the probability level of 1%

*** Significant at the probability level of 0.1%

3.2. PLS to predict GBM, and concentrations of N and NDF of forage

Cross-validated calibration results between CASI-3, ASD, and ASD_{CASI} reflectance spectra and GBM, N and NDF concentrations using FS-PLS, ISE-PLS and GA-PLS are shown in Table 2, with the selected number of wavebands (NW) and the selected NW as a percentage of the full-spectrum (NW% = NW / whole band [n = 34 for CASI-3 and ASD_{CASI}; n = 671 for ASD] × 100). The NW (NW%) ranged between 12 and 22 (35.29-64.71%) in CASI-3, 15 and 156 (2.27-30.26%) in ASD1nm and 5 and 22 (14.71-64.71%) in ASD_{CASI}.

Table 2: Performance of FS-PLS, ISE-PLS and GA-PLS regressions for predicting pasture parameters (GBM, N and NDF) using CASI-3 and ASD FieldSpec data of original 1 nm spectral resolution (ASD) and simulating CASI-3 spectral resolution (ASD_{CASI})

Pasture parameter	Regression method	CASI-3					ASD reflectance spectra (ASD_{1nm})					Simulated CASI spectra (ASD_{CASI})				
		NLV	R^2	RMSECV	NW	NW%	NLV	R^2	RMSECV	NW	NW%	NLV	R^2	RMSECV	NW	NW%
GBM (gDM m^{-2})	FSPLS	11	0.42	105.53	34	100.00	11	0.75	65.02	34	100.00	5	0.69	72.96	34	100.00
	ISEPLS	9	0.65	78.62	17	50.00	8	0.84	52.71	106	16.04	10	0.79	59.57	17	50.00
	GAPLS	9	0.69	72.68	17	50.00	11	0.86	48.70	92	13.92	8	0.80	59.00	4	11.76
N (%DM)	FSPLS	6	0.44	0.38	34	100.00	10	0.70	0.28	661	100.00	10	0.67	0.29	34	100.00
	ISEPLS	5	0.58	0.32	16	47.06	8	0.74	0.25	200	30.26	8	0.70	0.27	19	55.88
	GAPLS	8	0.61	0.31	12	35.29	5	0.75	0.25	15	2.27	5	0.73	0.26	5	14.71
NDF (%DM)	FSPLS	6	0.25	3.99	34	100.00	11	0.60	2.83	661	100.00	11	0.55	3.06	34	100.00
	ISEPLS	5	0.37	3.54	15	44.12	9	0.68	2.49	106	16.04	10	0.60	2.82	15	44.12
	GAPLS	14	0.50	3.28	22	64.71	13	0.73	2.34	156	23.60	11	0.66	2.61	22	64.71

NLV: number of latent variables in used PLS model; R^2: determination of cofficient in cross validated regression model; RMSECV: root mean squares error of cross validation; NW: number of waveband selected in the model; NW% percent ratio of NW to whole waveband.

The optimum NLV for all ranged between 5 and 14, determined as the lowest RMSECV values calculated from leave-one-out cross-validation, to avoid over-fitting of the model. The RMSECV values in FS-PLS, ISE-PLS and GA-PLS models for CASI-3, ASD, and ASD_{CASI} are shown in Figure 1. Narrow band ASD data set showed relatively lower RMSECV values than CASI-3 and ASD_{CASI} data sets for all pasture parameters. In the comparisons of PLS models, GA-PLS showed the best R^2 and lowest RMSECV values were obtained. These results confirm our previous study showing that the performance of PLS models can be improved through waveband s selection (Kawamura et al. 2010). Figure 2 shows the relationship between measured and cross-validated prediction values of pasture parameters using GA-PLS models on the data sets of CASI-3, ASD, and ASD_{CASI}. Overall, the best R^2 and lowest RMSECV values were obtained by ASD data set for GBM (R^2 = 0.86, RMSECV = 48.70), N (R^2 = 0.75, RMSECV = 0.25) and NDF (R^2 = 0.73, RMSECV = 2.34).

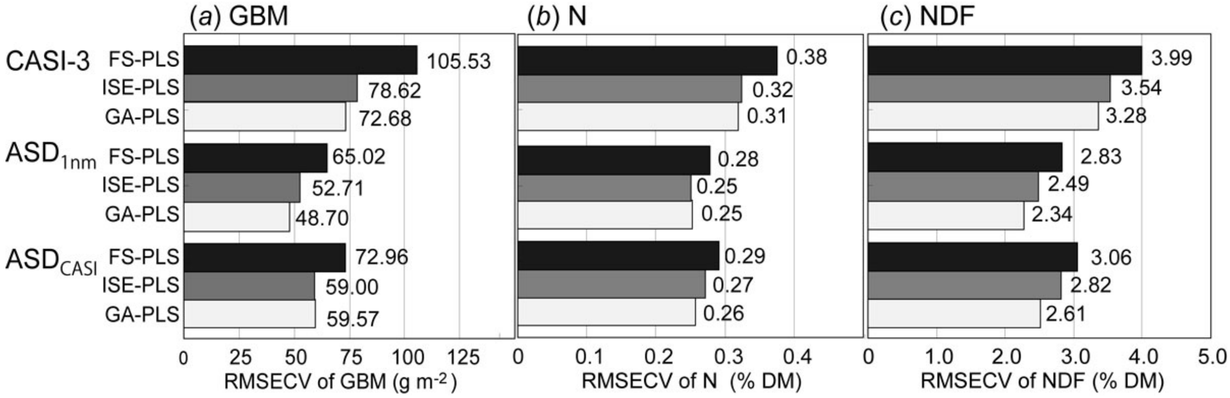

Figure 1: Root mean squares error of cross validation (RMSECV) from FS-PLS, ISE-PLS, and GA-PLS using CASI-3 (black bar), ASD FieldSpec (ASD_{1nm})(grey bar) and simulated CASI-3 (ASD_{CASI})(white bar) to estimate GBM (a), N (b) and NDF (c).

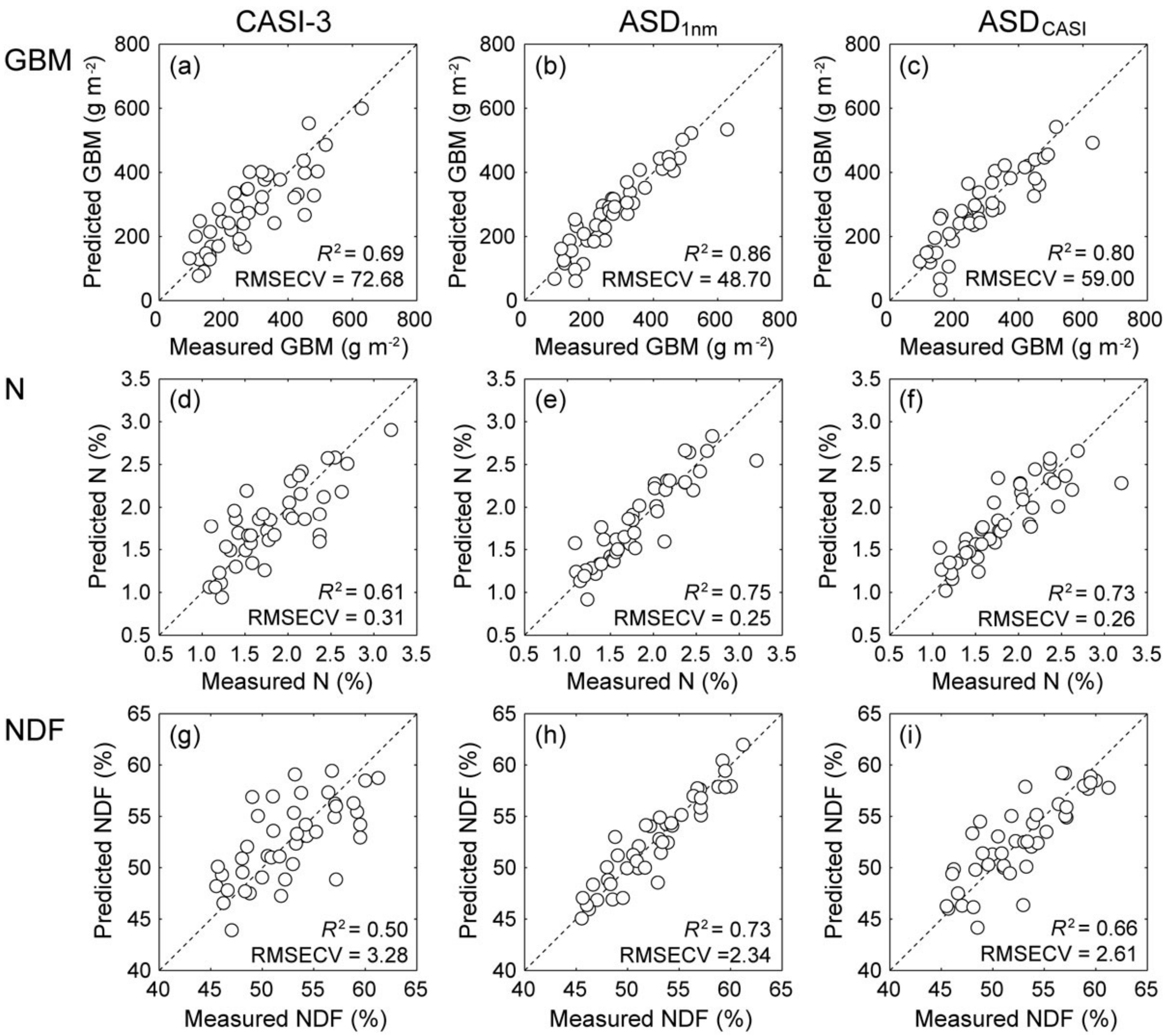

Figure 2: Measured and cross-validated predicted values of green forage biomass (GBM) (a, b, c), concentrations of nitrogen (N) (d, e, f), and neutral detergent fiber (NDF) (g, h, i) using genetic algorithms PLS (GA-PLS) regression on the CASI-3 hyperspectral data (left column), ASD FieldSpec derived original canopy reflectance data (ASD_{1nm}) (middle column), and simulated CASI-3 data from ASD (ASD_{CASI}) (right column)

3.3. Spatial distribution maps of GBM, and concentrations of N and NDF of forage

Applying the GA-PLS models on the CASI-3 image, spatial distribution maps of forage GBM and concentrations of N and NDF of herbage were generated, as shown in Figure 3. Here, CASI-3 True Color Image (R:G:B = 631 nm:551 nm:450 nm) was also added with the feature information of fence in subunit 1-3. To assess the quantitative and qualitative status of pasture between subunits using predicted pasture parameters, distribution of GBM and concentrations of N and NDF were calculated. The average ± SD values in subunit 1, 2, and 3 were, respectively, 313.5±86.7, 276.1±94.5, and 214.8±87.0 g m^{-2} for GBM, 1.9±0.6%, 1.8±0.7%, 2.4±0.7% for N, and 52.6±5.5%, 54.4±5.7%, and 50.5±5.9% for NDF. Such information might help farmer to make decision for efficient grazing management. Pasture is spatially heterogeneous in terms of vegetation and utilization by animals. In previous research on utilization by cattle at the same paddock in 2005 (Watanabe *et al.* 2010), behavior of two cows fitted with GPS units and bite counter collars showed similar tendencies in choosing locations and in the number of bites per day and per hour among the subunits in each month. The cows spent most of their time in subunit 1 in May and June, but as the time went by, the time in subunit 1 became short and was limited to daytime. In contrast, they stayed predominantly in subunits 2 and 3 at night in the latter half of the season. Throughout the season, the number of bites taken in subunit 1 was the greatest among all of the subunits. These results indicated that the aged, hilly sections (subunit 2 and 3) were mainly utilized as resting sites in the nighttime and were supplementarily grazed in the latter half of the season. In the present study, the subunit 1 showed greater herbage biomass. This finding might support that cattle predominantly preferred to graze in subunit 1. To efficient use of the paddock, an increase in grazing use of the aged, hilly sections will be required.

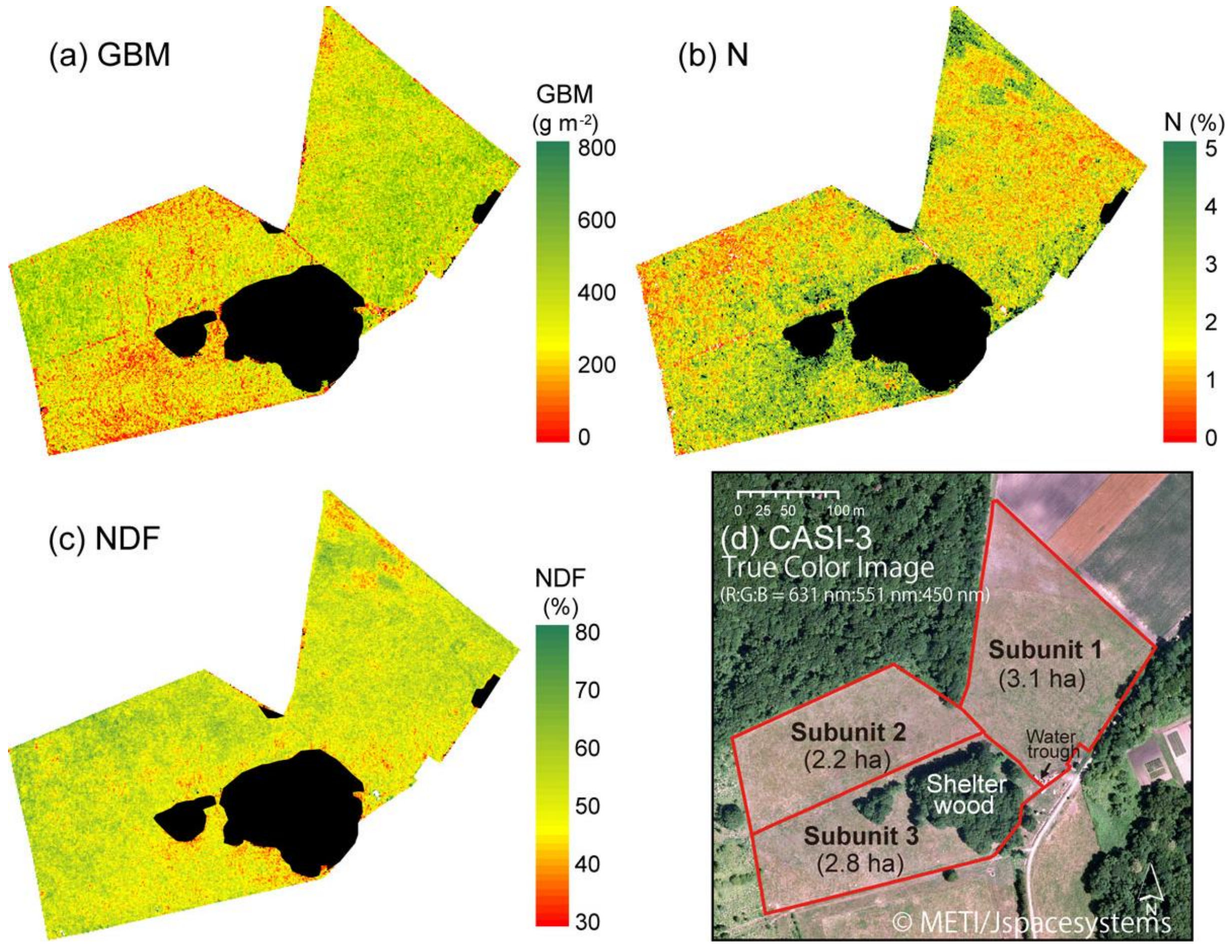

Figure 3: Spatial distribution maps of GBM (a), concentrations of N (b), and NDF (c) applied by the GAPLS models using CASI-3 hyperspectral imaging data, with CASI-3's True Color Image showing the experimental paddock (d)

4. CONCLUSIONS

In this study, we investigated the potential utility of airborne hyperspectral imaging with PLS regression for estimating herbage mass and forage quality in a grazed mixed pasture at Hokkaido, Japan. The results showed that herbage biomass and quality parameters can be predicted by airborne based hyperspectral imaging. Although the predictive accuracy was lower than that of ground based hyperspectral measurements, distribution maps of herbage mass and quality parameters are useful information to farmer for efficient grazing management.

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