Reducing Farmer Uncertainty in Spring Forage Harvests: Digital Image Analysis and Artificial Intelligence to Predict Alfalfa-Grass Stand Composition

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Introduction

- Harvest management decisions for spring forage harvests are critical given the small range in optimal fiber content (NDF) to make silage for lactating dairy cows (Cherney et al., 2006).
- Accurate prediction equations exist for estimating nutritive value and timing of spring alfalfa-grass harvest (Parsons et al., 2006). Available at http://www.forages.org (Figure 1).
- Required inputs include alfalfa maximum height, grass fraction in the sward, and targeted harvest NDF concentration.
- The weak link is grass fraction in the sward, which is difficult to estimate by visual observation alone. Parsons estimated grass fraction and determined known values for nearly 600 samples in 2004 ($y = 0.22 + 0.69x$, $R^2=0.43$, RMSE= 0.147).
- Misestimating composition by just 20% can result in late harvests by 5 or more days, potentially leading to NDF at harvest > 5 g kg^{-1} past target levels. This represents critical potential nutritive and economic losses for dairy farms.

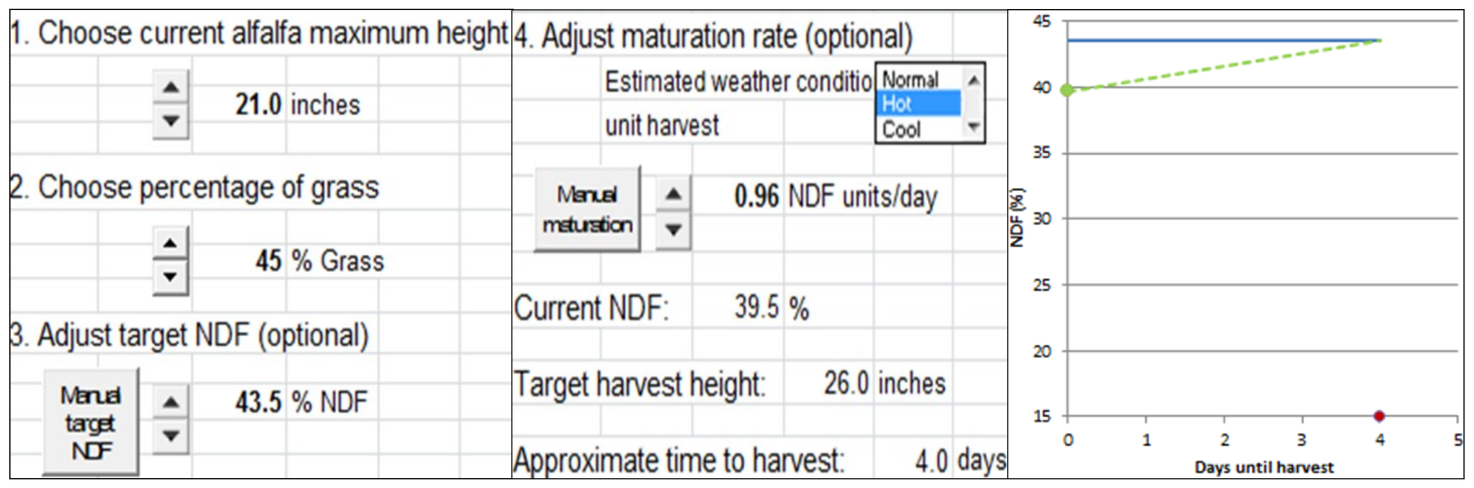

Figure 1: Screenshots from alfalfa-grass NDF tool on http://www.forages.org to estimate harvest timing for target NDF.

Objective

- Generate accurate stand composition estimates using an automated image processing system to improve performance of existing equations and help improve nutritive value of spring forage harvests in the Northeast.

Sampling Process

- Representative samples of mixed stands in farmers' fields were delineated using a 26" diameter hula-hoop.
- Digital images of samples were taken at 5-megapixel resolution.
- 580 samples were acquired in 2011 using one camera. Biomass within the hoop area was clipped at 10 cm above ground level.
- Grass species included orchardgrass (n=191), reed canarygrass (n=166), timothy (163), and quack (n=55).
- Alfalfa and grass max height and grass canopy height were recorded.
- 180 additional samples (60 each of timothy, orchardgrass, and reed canarygrass) were acquired in 2012 using four cameras including an IPhone 4.
- Known sward composition on a 60°C dry matter basis was determined for each sample by manually separating alfalfa and grass fractions and drying to stable weight.

Image Filtering Steps

- Hoop Extraction (Figure 2)
- Conversion to gray scale with an emphasis on green pixels (Figure 2)
- Tile Extraction: 64 x 64 pixel chunks cropped for analysis (Figure 3)
- 2-D fast Fourier transform and frequency aggregation (Figure 3)

Figure 2: Hoop extraction: a series of algorithms were defined to identify the hoop edges, extract the inner area of the hoop, and convert the resulting image to the gray scale with an emphasis on green pixels.

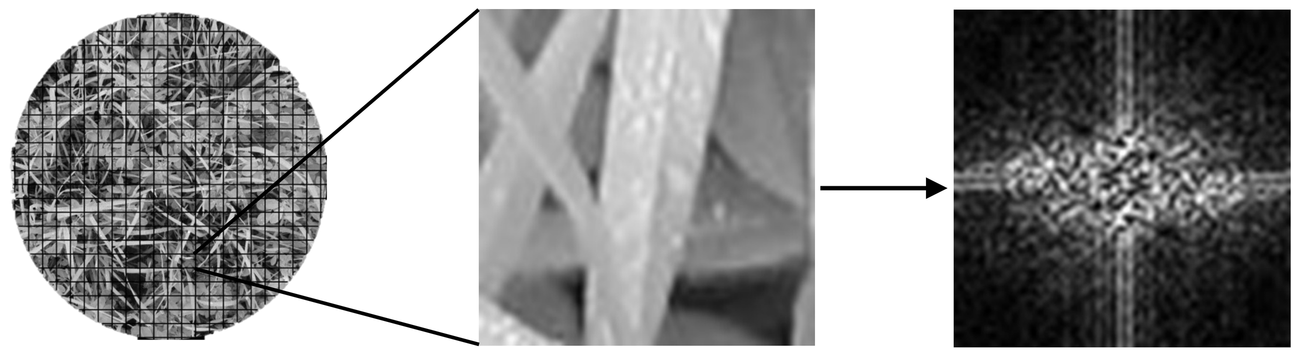

Figure 3: 64 x 64 pixel tiles were cropped for individual analysis. The fast Fourier algorithm was run on individual tiles. Frequencies under an arbitrary threshold (175) were ignored. For each tile, six axial frequencies were aggregated along both the x and y axes for processing by artificial intelligence (AI).

Estimating Stand Composition

- Multiple approaches have been tested (Table 1).
- Current approach: Support Vector Machine (SVM).
- Tiles within a subset of all 2011 images were classified as predominately grass (1), alfalfa (0) or unclassifiable.
- Classified tiles were used in SVM training using the LIBSVM open source package (Chang & Lin, 2011).
- Between 1,000 to 15,000 tiles were used to train each SVM run.
- Each trained SVM was applied to predict stand composition.
- Grass species-specific SVM training and testing was completed for timothy.

Table 1: Image analysis and artificial intelligence approaches tested.

Technique	Outcome
Geometric pattern matching	No discreet patterns in mixed stand images
Color separation	Grass and alfalfa shade of green too similar, especially under variable field conditions
Blob detection	Each piece must be a separate entity to work effectively
Tile method with fast Fourier transform (Polder et al., 2007)	Expressed frequencies differ for alfalfa and grass
+ Naïve Bayes Classifier AI (McRoberts et al., 2012)	Poor correlation between predicted and actual values
+ Fourier frequencies	Aggregated frequencies performed better than Naïve AI; collinearity problems with multivariate models
+ Support Vector Machine: LIBSVM open source package (Chang & Lin, 2011)	Preliminary results most promising to date

SVM Results

- Multiple SVM attempts to date including tests on the full 2011 set with all grass species (Table 2).
- Timothy set was trained with 3,000 to 10,000 tiles from 47 randomly selected images and tested on remaining 48 samples not used in training (Example of results in Figure 4). Only samples with good hoop extraction were used.

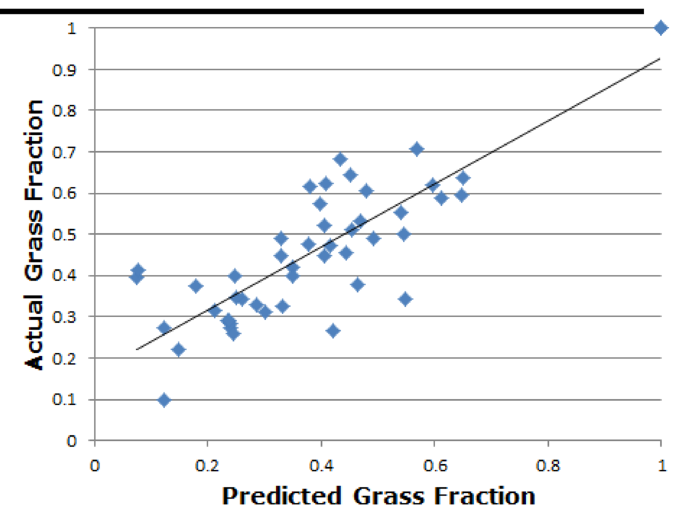

Figure 4: Actual versus predicted values for SVM with timothy samples, trained with 5,000 tiles. $y = 0.7661x + 0.1621$, $R^2 = 0.71$ driven by unity at 1, drops to 0.52 if excluded, but RMSE still at 0.098.

Table 2: Model results for actual versus predicted grass fractions for selected AI simulations.

Training tiles	Species	n	r^2	RMSE	p	Slope	Intercept
SVM Attempt 1							
4,000^{ab}	All	548	0.39	0.142	<0.0001	0.52	0.3
2,000^{ab}	Timothy	154	0.50	0.117	<0.0001	0.65	0.21
5,000^{ab}	Reed Canary	157	0.45	0.122	<0.0001	0.45	0.27
SVM Attempt 2							
4,000	Timothy	95	0.35	0.115	<0.0001	1.12	-0.05
4,000^{c}	Timothy	95	0.54	0.098	<0.0001	1.11^{d}	-0.63
SVM Attempt 3							
5,000^{a}	Timothy	48	0.71	0.098	<0.0001	0.77	0.16

a= alfalfa maximum height and grass canopy height were used in SVM training.
b= tiles from all grass species were used in SVM training; predictions were generated for all images.
c= alfalfa maximum height and grass canopy height were not used in SVM training, but were added to the statistical model as covariates.
d= The reported slope is the parameter estimate for SVM predicted values in the multivariate model.

Next Steps

- Continue grass species-specific SVM development on 2011 and 2012 datasets.
- Reconsider threshold levels for fast Fourier filters.
- Consider fast Fourier alternatives that could be applied individually or in combination (e.g., linear binary patterns, wavelet transformation).
- Attempt unsupervised SVM training.

Anticipated Outcome

- A farmer-friendly web application accurately estimating mixed stand composition, current NDF level, projected daily NDF rate of change, and target harvest date to achieve desired NDF level.
- If successful, materials needed to use the service will include:
- Hula-hoop (26" diameter) painted white.
- Digital camera or smartphone camera.
- Measuring stick (alfalfa max height, possibly grass canopy height and grass maximum height).
- Internet access.

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