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Use of satellite remote-sensing techniques to predict the variation of the nutritional composition of corn (*Zea mays* L) for silage

Gonzalo Ferreira[1]*, Eleonor L Cayford[1], Leyang Feng[2], Yang Shao[2], Marcos Isla-Casares[3]

[1]Department of Dairy Science, Virginia Polytechnic Institute and State University, Blacksburg, 24061, USA
[2]Geography Department, Virginia Polytechnic Institute and State University, Blacksburg 24061, USA
[3]Gestión de Precisión, Carriego 1256, (1664) Pilar, Argentina
*Corresponding author: E-mail: gonf@vt.edu

Abstract

The nutritional composition of corn (*Zea mays* L) silage can vary substantially within a same silo. Environmental differences within the cornfield could contribute to this variability. We explored using green vegetation index maps, known as normalized difference vegetation index (NDVI) maps, to identify differences in the nutritional composition of corn at the field level. We hypothesized that the nutritional composition of the corn plant differs within the cornfield according to the vegetation index maps as detected by satellite remote-sensing techniques. Three cornfields from 3 commercial dairy farms located within the state of Virginia were utilized in this study. Landsat satellite data were obtained from the US Geological Survey to develop NDVI maps. Each cornfield was segregated in 3 regions classified as low NDVI, mid NDVI, and high NDVI. Corn plants from each region were harvested to determine their nutritional composition. At harvesting, corn plants were cut, weighed, chopped, and analyzed in the laboratory. Data were analyzed as for a complete block design, where fields and NDVI regions were considered blocks and treatments, respectively. The concentrations of ash (40 g kg^{-1}), crude protein (102 g kg^{-1}), neutral detergent fiber (398 g kg^{-1}), acid detergent fiber (232 g kg^{-1}), acid detergent lignin (14 g kg^{-1}), and starch (304 g kg^{-1}) did not differ at different NDVI regions. In our study none of the cornfields seemed to be environmentally stressed during the growing season of 2014. Therefore, it is plausible that the intrinsic variation of the cornfields was minimum due to the adequate growing conditions.

Keywords: variation, vegetation index, corn silage, nutritional composition

Abbreviations: ADF = acid detergent fiber; ADL = acid detergent lignin; CP = crude protein; DM = dry matter; NDF = neutral detergent fiber; NDVI = normalized difference vegetative index.

Introduction

In dairy farming systems, inaccurate feeding may impair productivity, profitability, or both. Inaccurate feeding occurs when diets are formulated without knowing the actual nutritional composition of feed ingredients, so that inadequate amounts of nutrients are fed relative to the animal's requirements (NRC, 2001; St-Pierre and Weiss, 2015). For example, overestimating the concentration of protein for alfalfa silage might limit milk production by dairy cows, whereas underestimating the concentration of protein in alfalfa silage can unnecessarily increase feed costs and the amounts of N released to the environment.

Even though the nutritional composition of feed ingredients can be determined in a laboratory, the estimated composition is subjected to several sources of variation (St-Pierre and Weiss, 2015). Weiss et al (2012) measured the nutritional composition of corn silages on a daily basis for 14 consecutive days in 8 farms and reported that the concentration of dry matter (DM), neutral detergent fiber (NDF), and starch varied as much as 104, 112, and 277 g kg^{-1} units within the same silo, respectively. Sources of this day-to-day variation can be related to analytical procedures and sampling techniques (i.e., extrinsic variation), or to actual or intrinsic variation of the silage (St-Pierre and Weiss, 2015). The latter source of variation is typically attributed to differences in plant genetics, environment, management practices, or their combinations.

Environmental diversity within a field, caused by differences in soil fertility or topography, could potentially affect DM yields and the nutritional composition of homegrown forages for silage. In theory, a more precise feeding could be accomplished if the intrinsic variation of homegrown forages could be predicted. For example, if the heterogeneity of the topography would result in corn silage with variable nutritional composition, then identifying regions with similar nutritional compositions could help to harvest and ensile the crop according to this variation, therefore reducing the day-to-day variation of the nutritional composition of the corn silage.

Green vegetation index maps are spatial repre-

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sentations of the vegetative biomass at the crop level. Normalized difference vegetation index (NDVI) is one of the commonly used vegetation indices for biomass assessment and can be routinely derived from satellite remote-sensing data (Hayes and Decker, 1996; Gutierrez et al, 2010; Zhong et al, 2013). Canopy reflectance properties are based on the absorption of light at specific wavelengths associated with plant characteristics (Gutierrez et al, 2010), such as chlorophyll concentration (Mkhabela et al, 2005). A vegetation index, represented by a NDVI value, quantifies the greenness and vigor of vegetation (Hayes and Decker, 1996). For example, healthy green vegetation normally has the highest NDVI values, whereas stressed vegetation or vegetation with small leaf areas have lower NDVI values. This technology enables an indirect assessment of canopy biomass, leaf area index, potential photosynthetic capacity of the crop, and even grain yield (Hayes and Decker, 1996; Mkhabela et al, 2005; Gutierrez et al, 2010).

For this field study we proposed an interdisciplinary approach to predict the intrinsic variation of the nutritional composition in corn for silage. Specifically, we proposed using green vegetation index maps to identify differences in the nutritional composition of corn at the field level. Because a high NDVI is related to vigorous and non-stressed plants, we hypothesized that the concentrations of fiber and starch would be lower and higher, respectively, in the areas with the higher NDVI values, as detected by satellite remote-sensing techniques. Therefore, the objective of this study was to evaluate the nutritional composition from corn plants selected in different regions within a cornfield according to the vegetation index maps.

Materials and Methods

Cornfields and climate data

Three cornfields located in Blacksburg, Glade Spring and Chatham, Virginia, were utilized in this study. The first cornfield belongs to a 250 cow research dairy farm, and has an area of 25 hectares. The second cornfield belongs to a 700 cow commercial dairy farm, and has an area of 100 hectares. The third cornfield belongs to an 800 cow commercial dairy farm, and has an area of 55 hectares. All cornfields were evaluated during the growing season of 2014. Corn crops were managed according to the common practices for each farm.

Data for temperatures (average, maximum and minimum) and precipitations during the growing season were obtained from Weather Underground (www.wunderground.com) for Blacksburg, Glade Spring, and Rocky Mount (closest weather station to Chatham), VA (Table 1). Historical climate data were obtained from the Southeast Regional Climate Center (www.sercc.com).

Normalized difference vegetative index

Landsat images were obtained from the US Geological Survey online EarthExplorer system (www.earthexplorer.usgs.gov). Two types of data were used in this research: land surface reflectance from Landsat 7 Enhanced Thematic Mapper (L7 ETM+) im-

Table 1 - Temperatures and precipitations during the growing season at 3 locations within the state of Virginia[1].

	Blacksburg	Glade Spring	Rocky Mount
Mean Temperature, °C			
April	11.7 (10.7)	15.0 (11.3)	13.9 (13.0)
May	17.2 (15.4)	18.3 (15.9)	20.0 (17.7)
June	21.1 (19.6)	22.8 (19.7)	23.9 (21.9)
July	21.7 (21.8)	22.2 (21.5)	23.9 (24.0)
August	20.6 (21.2)	22.2 (21.3)	22.2 (23.3)
Maximum Temperature, °C			
April	18.9 (17.7)	21.7 (19.1)	20.0 (20.2)
May	24.4 (22.3)	25.0 (23.5)	26.1 (24.8)
June	27.8 (26.1)	28.3 (26.8)	29.4 (28.5)
July	27.2 (28.1)	27.2 (28.2)	28.9 (30.2)
August	25.6 (27.7)	27.2 (28.2)	26.7 (29.4)
Minimum Temperature, °C			
April	3.9 (3.8)	8.3 (3.6)	7.2 (5.8)
May	10.0 (8.6)	12.2 (8.3)	13.3 (10.7)
June	10.0 (13.1)	17.8 (12.7)	17.8 (15.4)
July	15.6 (15.4)	17.2 (14.9)	18.3 (17.8)
August	15.0 (14.8)	17.2 (14.3)	17.8 (17.1)
Precipitations, mm			
April	105 (91)	61 (95)	106 (90)
May	68 (104)	59 (116)	60 (98)
June	78 (93)	102 (102)	77 (103)
July	49 (102)	118 (120)	86 (121)
August	151 (88)	106 (97)	166 (107)
April-August	451 (478)	446 (529)	496 (520)

[1]Values within parentheses represent historical climatic data.

ages, and Landsat 8 Operational Land Imager (OLI/TIRS) images. Spatial resolution of both Landsat 7 and Landsat 8 images is 30 meters. Land surface reflectance for Landsat 7 products was generated using Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) from US National Aeronautics and Space Administration (www.ledapsweb.nascom.nasa.gov). Atmospheric correction was performed during LEDAPS generation to reduce the effect of atmosphere on land surface reflectance; therefore the value of each pixel was rescaled between -2,000 and 16,000. The Landsat 8 Level 1 GeoTiff data were delivered as 16-bit unsigned integer format scaled between 1 and 65,535. All Landsat images were rectified to the Universal Transverse Mercator (UTM) projection system (ellipsoid GRS80, datum NAD83, zone 17). Visual assessment of cloud contamination in and around the 3 fields was made using red and near-infrared band imagery (bands 3 and 4, respectively, for Landsat 7 data, and bands 4 and 5, respectively, for Landsat 8 data). Field boundaries were then delimited for each of the 3 fields for further NDVI calculation.

Normalized difference vegetation index maps were calculated according to the following formula:

$$NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}}$$

where R_{NIR} and R_{RED} are the spectral reflectance in the near infrared and red bands, respectively. This NDVI equation produces values in the range from -1 to 1, where positive values indicate vegetated areas and negative values represent non-vegetated surface areas, such as bare soil, water, clouds, and snow (Hayes and Decker, 1996). The NDVI values for each pixel of all images were calculated under ArcGIS/ArcPy environment. These values were categorized within each field as low NDVI, mid NDVI, and high NDVI (i.e., relative values), which were represented by red, yellow, and green pixels, respectively, within the vegetation index map (Figure 1).

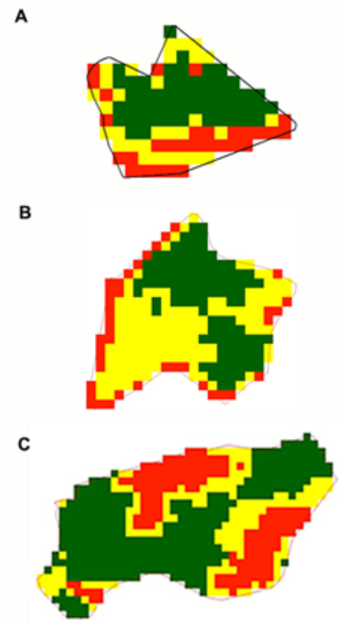

Figure 1 - Vegetation index maps of cornfields destined for silage, according to their normalized difference vegetative index (NDVI) values. Colors represent low (red), mid (yellow), and high (green) NDVI values. Cornfields were located in Montgomery (A), Pittsylvania (B), and Washington (C) counties (Virginia), respectively.

Sample collection

This project was performed respecting crop management practices from each of the three dairy farms. Considering logistic and climatic circumstances, and to ensure we obtained our samples before farmers harvested and ensiled their crops, we targeted to harvest as soon as possible after reaching an early-dent stage of maturity.

Sample collection involved: 1) walking through the standing corn crop from a field-reaching-point to each of the 3 sampling regions, 2) collecting 3 subsamples of corn plants per sampling region (see below), and 3) carrying these subsamples back to the field-reaching-point. Based on this approach, the sampling regions within each field were arbitrarily selected to minimize the walking distance between the field-reaching-point and the sampling regions. Coordinates for each sampling region within each field were obtained using Google Earth (Google Inc., Mountain View, CA). At sampling time, each of the 3 sampling regions within each field was reached using a hand-held global positioning system (Garmin International, Inc, Olathe, KS).

Sample collection occurred on August 14^{th}, August 30^{th}, and September 9^{th} 2014 for Chatham, Glade Spring, and Blacksburg, respectively. At harvesting, 10 consecutive corn plants at 3 randomly selected spots within each sampling region were cut by hand at 15 cm above ground. Each of the 10-plant bundles was considered a subsample within each of the 3 sampling regions. Whole plants were weighed and chopped with a Stanley CH2 wood chipper (GXi Outdoor Power, LLC, Clayton, NC). After mixing thoroughly within a barrel, a sample of the chopped material was placed in a bag, immediately placed in a cooler with dry ice, and transferred to the laboratory for storage at -20°C.

Laboratory analyses

Chopped samples were thawed, dried at 55°C in a forced-air drying oven until constant weight to determine DM concentration and plant biomass, and ground to pass through a 1-mm screen of a Wiley mill (Thomas Scientific, Swedesboro, NJ). Crude protein concentration was calculated as percent N x 6.25 after combustion analysis (AOAC 990.03) using a Vario El Cube CN analyzer (Elementar Americas, Inc, Mount Laurel, NJ). Neutral detergent fiber concentration was determined using the $Ankom^{200}$ Fiber Analyzer (Ankom Technology, Macedon, NY) with sodium sulfite and α-amylase (Ankom Technology) as described by Ferreira and Mertens (2007). ADF and ADL concentrations were determined sequentially. ADF concentration was determined using the Ankom^{200} Fiber Analyzer as described by Ferreira and Mertens (2007). After determining ADF weights, residues were incubated for 3 h and at 25°C in 72% sulfuric acid within a 4-l jar that was placed in a DaisyII Incubator (Ankom Technology). Starch concentration was determined using the acetate buffer method of Hall (2009) with α-amylase from *Bacillus licheniformis* (FAA, Ankom Technology) and amyloglucosidase from *Aspergillus niger* (E-AMGDF, Megazyme International, Wicklow, Ireland). Ash concentration was determined after burning feed samples in a furnace for 3 h at 600°C (AOAC 942.05).

Statistical analysis

Data were analyzed with the Mixed Procedure of SAS (SAS version 9.3, SAS Institute, Inc, Cary, NC) as for a complete block design. The statistical model included the random effect of field or block (degrees of freedom = 2), the fixed effect of NDVI (degrees of freedom = 2), and the field by NDVI interaction, which was considered as the residual error (degrees of freedom = 4). Each observation consisted of the mean composition of 3 subsamples (i.e., 10-plant bundle) within a single NDVI region.

Considering standard deviations equal to 25.6 g kg^{-1} for NDF concentration and 22.8 g kg^{-1} for starch concentration (Ferreira et al, 2014), a statistical power of 0.80 and a probability of committing type 1 error of 0.10, this project would detect significant differences greater than 63 g kg^{-1} for NDF and 57 g kg^{-1} for starch. Therefore, if intrinsic variation would exist within the cornfields, there is sufficient statistical power to detect the differences in NDF and starch concentrations reported previously (112 and 277 g kg^{-1} for NDF and starch, respectively; Weiss et al, 2012).

Results

Climate data (Table 1) show that the growing conditions were normal relative to historical series. Mean temperatures were slightly higher than normal in late spring for Blacksburg and Rocky Mount, although these were below normal in early summer. Mean temperatures were slightly higher than normal throughout the whole growing season in Glade Spring, although these were not substantially higher. Precipitations were 478, 529, and 520 for Blacksburg, Glade Spring, and Rocky Mount, respectively (Table 1). These values represent 94, 84, and 95% of the normal precipitations.

The concentrations of ash (40 g kg^{-1}; $P > 0.69$), CP (102 g kg^{-1}; $P > 0.38$), NDF (398 g kg^{-1}; $P > 0.91$), ADF (232 g kg^{-1}; $P > 0.33$), ADL (14 g kg^{-1}; $P > 0.13$), and starch (304 g kg^{-1}; $P > 0.99$) did not differ between NDVI regions (Table 2). In addition to this, fresh plant biomass (903 g $plant^{-1}$; $P > 0.62$), DM concentration (298 g kg^{-1}; $P > 0.56$), and dry plant biomass (266 g $plant^{-1}$; $P > 0.79$) did not differ among NDVI regions (Table 2).

Discussion

Contrary to our expectations, the nutritional composition of corn plants did not differ between areas of different NDVI values. The lack of statistical differences in nutritional composition could be attributed to the statistical power of the design or to a minimum intrinsic variation between areas of different NDVI values. As mentioned before, the experimental design had sufficient statistical power to detect differences in NDF and starch concentrations previously reported (112 and 277 g kg^{-1} for NDF and starch, respectively; Weiss et al, 2012). Conversely, our data show a minimum difference in nutritional composition between areas of different NDVI values (less than 11 g kg^{-1} for all nutritional entities). Therefore, we attribute the lack of statistical difference between areas of different NDVI values to a minimum intrinsic variation of the composition of the plants in a same cornfield.

Wang et al (2011) concluded that NDVI could assess the concentration of N in leaves of both normal and water-stressed corn plants. In our study none of the cornfields seemed to be environmentally stressed during the growing season of 2014. This observation is supported by climatic data showing non-extreme temperatures and adequate precipitations during the growing season (Table 1). Therefore, it is plausible that the intrinsic variation of the cornfields was minimum due to the adequate growing conditions. Alternatively, it is also possible, and somehow surprising, that the intrinsic variation of corn silage is typically low for ash, CP, NDF, ADF, ADL, and starch. Cox and Cherney (2001) reported that NDF concentration of corn silage was only 13 g kg^{-1} more when corn was planted at 116,000 plants ha^{-1} than when planted at 80,000 plants ha^{-1}. Marsalis et al (2010) observed similar CP and NDF concentrations when both, corn and forage sorghum, were planted at different populations. Similarly, Ferreira et al (2014) recently reported similar ash, CP, NDF, ADF, ADL, and starch concentrations when corn was planted at different densities. In regards to N fertilization, Marsalis et al (2010) reported similar NDF concentrations for both corn and sorghum when grown with different N fertilization doses (218 vs. 291 kg N ha^{-1} for corn and 106 vs. 140 kg N ha^{-1} for sorghum). Islam et al (2012) also reported similar NDF concentrations in corn plants from crops grown with different N fertilization doses (both pre- and post-seeding). These observations agree with Sheaffer et al (2006) who reported that N fertilization had little effect on forage quality variables except for CP concentration; despite having a positive effect on grain and whole plant DM yields. In regards to water status, Islam et al (2012) also evaluated the effect of irrigation on DM yield and nutritional composition of corn silage. Interestingly, while irriga-

Table 2 - Plant weight and nutritional composition[1] (DM basis) of green-chopped corn according to the normalized difference vegetative index (NDVI) of the fields where it was harvested.

	Low NDVI	Mid NDVI	High NDVI	SEM	P value
Plant wet weight, g plant^{-1}	957	830	924	105	0.71
DM, g kg^{-1}	292	304	297	13.0	0.38
Plant dry weight, g plant^{-1}	273	253	273	26	0.75
Ash, g kg^{-1}	41	41	39	2.4	0.77
CP, g kg^{-1}	98	100	107	7.9	0.38
NDF, g kg^{-1}	397	401	396	27.3	0.97
ADF, g kg^{-1}	234	237	226	19.3	0.59
ADL, g kg^{-1}	11	14	16	3.7	0.55
Starch, g kg^{-1}	304	296	296	21.4	0.92

[1]DM = dry matter; CP = crude protein; NDF = neutral detergent fiber; ADF = acid detergent fiber; ADL = acid detergent lignin.

tion increased DM yields from 9.3 to 23.8 ton ha^{-1} and grain yields from 856 to 7,497 kg ha^{-1}, the NDF concentrations of corn silages differed by only 31 g kg^{-1}. Observations from our and previous studies (Marsalis et al, 2010; Islam et al, 2012; Ferreira et al, 2014) have two implications. First, the intrinsic variation of corn for silage might be less than typically expected under non-stressing conditions. Second, field variation in grain yield might not be highly related to forage quality (Islam et al, 2012). The number of kernels per unit of area is the main determinant of grain yield. For corn silage, both the stover and the grain yields determine corn silage yield and quality. Factors affecting grain yield may affect stover yield as well (Sheaffer et al, 2006; Kiziloglu et al, 2009; Islam et al, 2012), therefore, affecting minimally the nutritional composition of the whole plant.

Remote-sensing techniques have been utilized to relate NDVI with canopy (Hong et al, 2004) and grain yields (Teal et al, 2006). Hong et al (2004) reported a positive relationship (R^2 = 0.61) between NDVI corn canopy of through the growing season, although this relationship depended on soil background and plant stand. Teal et al (2006) reported a positive and high relationship (R^2 = 0.77) between NDVI and grain yield, although this relationship depended on the phenological stage of the corn crop. In our study, the goal was to use satellite remote-sensing techniques to predict variability in nutritional composition and not on biomass yield. However, based on the similar plant weights (Table 2) there was no relationship between NDVI and biomass yield.

In the study from Teal et al (2006) the highest relationship between NDVI and grain yield was observed when NDVI was estimated at the 8-leaf stage (V8) of the crop. According to the authors, yield potential was not accurately determined at late vegetative stages of phenology (V9 to V11). For our study we used NDVI maps developed at reproductive stages, assuming that developing NDVI maps closer to harvesting time would better reflect the relationship between NDVI and nutritional quality of corn for silage. It may be possible that this was an erroneous use of this technology, therefore explaining the lack of relationship between NDVI and the nutritional quality of corn for silage.

Conclusions

To our knowledge, this is the first study exploring the use of satellite remote-sensing techniques to predict the variability of the nutritional composition of corn plants destined for silage. Based on our data, the nutritional composition of corn plants did not differ with NDVI. The main reason to this observation seemed to be the very low variability in nutritional composition of corn plants, likely explained by the adequate climatic condition during the growing season. Despite this possibility, we cannot discard an erroneous use of this technology when generating NDVI at reproductive, and not vegetative, phenological stages. Future studies should evaluate whether the relationship between NDVI and nutritional composition is dependent of the phenological stage at which the NDVI maps are developed. Overall, whether satellite remote-sensing techniques are useful tools to predict the variability of the nutritional composition of corn for silage still needs to be elucidated.

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