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USING NDVI AS A PASTURE MANAGEMENT TOOL

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ABSTRACT OF THESIS

USING NDVI AS A PASTURE MANAGEMENT TOOL

Maintaining forage availability is challenging for managers of grazing systems, especially in spatially heterogeneous swards. Remote sensing may help to overcome this problem. The objectives of this study were to (i) determine a method by which NDVI may be calibrated to estimate biomass, (ii) determine if NDVI can be used to assess spatial variability of yield in extensive grasslands, and (iii) to determine if NDVI can be used to evaluate grazing systems. We found that the calibration of NDVI values for the estimation of biomass was better correlated with the destructive harvesting procedure (R^2 = 0.68) but far more laborious and time-consuming than estimation of biomass from the rising plate meter (R^2 = 0.54). Semivariograms revealed that sampling at a 0.76 m distance provided information about the spatial variability structure of NDVI values from grazed swards. Frequency distributions of sward biomass derived from NDVI reflected foraging strategies of cattle. Negative skewness and high kurtosis of histograms indicated selective grazing, while positive skewness and low kurtosis indicated the opposite. Histograms also allowed for estimation of available forage within each field. We concluded that grassland biomass may be derived from high resolution NDVI and RPM data and used to evaluate condition of grassland landscapes and aid decision-making of managed grazing systems.

KEYWORDS: NDVI, Remote Sensing, Biomass Estimation, Histogram, Available Forage

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USING NDVI AS A PASTURE MANAGEMENT TOOL

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THESIS

Ernest Scott Flynn

The Graduate School

University of Kentucky

2006

USING NDVI AS A PASTURE MANAGEMENT TOOL

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THESIS

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A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in the
College of Agriculture
at the University of Kentucky

By

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Lexington, Kentucky

Director: Dr. Charles T. Dougherty, Professor of Crop Science

Lexington, Kentucky

2006

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Chapter 1

Maintaining forage availability at a level that maximizes profits is challenging for managers of grassland livestock systems, especially when they are working with spatially heterogeneous swards. Numerous methods of estimating pasture biomass have been developed, but most tend to be operator-dependent, labor intensive, costly, and invariably require separate calibrations for different species, seasons, pasture management strategies, and geographical location (Haydock and Shaw, 1975; Gourley and McGowan, 1991; Aiken and Bransby, 1992; Harmoney et al., 1997; Sanderson et al., 2001; Martin et al., 2005). The most complex problem in the measurement of biomass, however, is finding appropriate sampling procedures that account for spatial variability. Although mean forage mass is a primary descriptor of grazing systems, information about spatial distribution of that biomass may be more important. Maps depicting how yield is spatially distributed allow for the identification of chronically-poor areas of productivity, the estimation of the impact of additional inputs (e.g. fertilizer, irrigation, pesticides, pasture renovation), and may lead the way for more functional site-specific pasture and grazing management decisions (Hill et al., 1999).

Frequency distributions are another important criterion for describing spatial variability. By examining the frequency distribution of biomass, inferences may be made about the causes and effects of spatial heterogeneity of swards on grazing systems, through facets such as grazing behavior and forage utilization. For example, proportions of under and overgrazed areas within a sward are the direct results of selective grazing by livestock (Aiken et al., 1997; Cid and Brizuela, 1998; Correll et al., 2003). As swards are depleted, grazing animals may be forced to become less selective of the area in which they graze. The areas they are forced to graze usually consist of less palatable and sometimes less digestible forages such as those found in over mature patches of herbage, and patches of tall grass found near recently deposited fecal material (Aiken et al., 1997; Cid and Brizuela, 1998; Correll et al., 2003). Therefore, the type of frequency distribution exhibited for biomass (normal, double-normal, log normal, etc.) (Barthram et al., 2005) may allow for refinement of grazing management and characterization of patterns of diet selectivity.

Remote sensing of grasslands at high resolutions using the normalized difference vegetation index (NDVI) is a feasible approach to handling the temporal and spatial variability of sward variables for use in management of grazing systems. The normalized difference vegetation index is correlated with biomass when the Leaf Area Index (LAI) is less than 3 (Weiser et al., 1986, and Serrano et al., 2000) and when collected with ground-based platforms, aircraft, or satellites, offers a non-destructive and minimally invasive method of sampling. In well-managed grazing systems, NDVI and estimates of biomass derived from NDVI are good indicators of pasture productivity. Both strong and moderate correlations have been found between NDVI and biomass of shortgrass steepes (R^2=0.66) (Todd et al., 1998); alfalfa (*Medicago sativa*) (R^2=0.89) (Mitchell et al., 1990), and winter wheat (*Triticum aestivum*) (R^2=0.60-0.78) (Moges et al., 2004). NDVI has also been used to evaluate vegetation condition of entire countries. In Mongolia, for example, NDVI derived from NOAA/AVHRR data have been used to evaluate pasture growth and to monitor the long-term changes in pasture productivity over a 20-year period (Magsar, 2004). Overall, NDVI has proven to be useful in evaluating yield in many agronomic crops and an excellent decision-making tool for producers.

High-resolution NDVI data may be used to evaluate large scale grazing systems. To our knowledge, little has been done to evaluate NDVI data as a grazing management tool or to assess its use in describing the spatial variability within grazed swards. It has also come to our attention that few methods exist by which NDVI may be calibrated for biomass or pasture variables used in management of grazing systems.

The objectives of this study were to, (i) determine a method by which NDVI may be calibrated to estimate biomass, (ii) determine if NDVI can be used to assess spatial variability of yield in extensive grasslands, and (iii) to determine if NDVI can be used to manage grazing systems in terms of calculating available forage and evaluating stocking rates.

Chapter 2

Importance of Biomass Estimates

        Estimates of pasture biomass are needed by managers of livestock grazing systems to utilize their grassland resources more efficiently (Harmoney et al., 1997; Sanderson et al., 2001). For example, pasture biomass is the single most important factor in setting stocking rate, stocking density and herbage allowance in grazing systems (Gourley and McGowan, 1991; Aiken and Bransby, 1992). Herbage estimates are also used in making management decisions that improve productivity and overall profitability of grazing systems by properly allocating resources, such as labor and capital. Grazing dairy farmers, for example, use these estimates as tools to help plan grassland use, timing of application and quantity of manure and fertilize supplied, timing of grazing, and mowing and adaptation of paddock size (Schut et al., 2005). Knowing the amount of available forage on a large scale throughout the year allows producers to make well-informed management decisions that increase profitability, while maintaining a forage base that meets short term animal production goals or supplies the nutritional needs of livestock year-around.

Limitations of Current Methods of Estimation

Direct Harvesting

        Direct harvesting is currently the best and most widely used method of determining grassland biomass eventhough it is costly, time-consuming, and destructive. Using this method allows individual samples to be measured accurately; however, the samples collected only represent a small area out of a large and highly variable sward (Haydock and Shaw, 1975; Harmoney et al., 1997; Sanderson et al., 2001; Martin et al., 2005). Because the problem lies with the variability of the sward and not with the precision of the measurement, it is better to take many samples with less precision than a few measured precisely (Haydock and Shaw, 1975). To increase the number of samples taken and to reduce time spent in sampling, faster non-destructive methods, such as the capacitance meter, rising plate meter (RPM), Robel pole, disk meter, sward stick, leaf canopy analyzer, and visual rating methods have been developed (Davies et al., 1993).

Although these methods overcome some problems, they introduce a host of others, such as calibration errors, operator variability, and incorrect applications that may make them invalid for intended applications.

Universal Calibrations

Many commercially available biomass sampling devices are accompanied by universal calibration equations that may be misapplied if they were developed in different regions with different vegetation. Sanderson et al. (2001) observed poor relationships between pasture biomass and biomass calculated with universal equations on grass-legume mixtures for commercial capacitance meters ($R^2 = 0.19$), rising plate meters (RPM) ($R^2 = 0.31$) and sward sticks ($R^2 = 0.16$). They concluded that, at the very least, regional specific calibrations should be made to improve accuracy and precision. Earle and McGowan (1979), while working with the rising plate meter, came to the same conclusion.

Observational Error

Differences among observers show an inability of indirect methods to predict biomass. Aiken and Bransby (1992) found differences between observers in their calibration of disk meters ($P \leq 0.001$) and a tendency to overestimate biomass when observers selected areas of "average" forage mass for measurement ($P \leq 0.001$). They also recorded differences among observers when estimating biomass of pastures grazed at varying stocking rates ($P \leq 0.001$). Observer variation was attributed to difficulties in estimating relative proportions of over- and under-grazed areas, the choice of sites for calibration, and an inadequate number of samples taken for calibration. Haydock and Shaw (1975), when using "The Comparative Yield Method", also detected variations among observers as well as the same tendency to overestimate mean yields.

Sward Density

Plant dry matter density, although taken into consideration with other designs, may not be adequately addressed by the sward stick and may account for poor correlations with pasture biomass (Harmoney et al., 1997). Although comparable results

have been obtained when comparing the RPM ($R^2 = 0.49$) and the sward stick ($R^2 = 0.52$) (Murphy et al., 1995), the sward stick required 10-fold more readings. When using a sward stick, one assumes a uniform plant density throughout the pasture.

Each indirect method of yield estimation may have an appealing attribute or attributes. Many methods tend to work quite well when properly calibrated and sample numbers are sufficient to overcome biases. However, indirect methods do not assess spatial variability within a pasture unless many sward areas are measured. Although intensive sampling is possible, the time, effort, and labor costs may not be justified from a grassland management standpoint.

Spatial Variability

When estimating pasture biomass, the most complex task is to determine how to sample so that the grassland is accurately represented and a true description of spatial variability is achieved (Tarr et al., 2005). It is useful to know the average pasture biomass but in a spatially heterogeneous system the spatial distribution may be more important to managers of grazing systems (Correll et al., 2003).

Patch Grazing

Over an extended period, grasslands grazed at low stocking rates are characterized as a mosaic of undergrazed and overgrazed patches that are the direct result of selective grazing by animals (Cid and Brizuela, 1998; Hirata, 2000; Correll et al., 2003; Barthram et al., 2005). The depiction of spatial variability in map form allows the identification of chronically-poor areas of productivity, the estimation of the impact of additional inputs (e.g. fertilizer, irrigation, pesticides, pasture renovation), and may lead the way for more functional site-specific pasture and grazing management decisions (Hill et al., 1999).

Histograms

By examining the frequency distribution of biomass, inferences may be made about the spatial heterogeneity of swards and its effects on grazing systems through facets such as grazing behavior and forage utilization. As previously described, the proportions of under and overgrazed areas within a sward are the direct result of selective

grazing by livestock. As swards are depleted, grazing animals become less selective of the area in which they graze with the possible exception of patches of tall grass around recently deposited fecal material (Aiken et al., 1997; Cid and Brizuela, 1998; Correll et al., 2003). Because the frequency distribution of grassland biomass may characterize a grazing system, scientists have attempted to define distribution patterns as indicators of pasture utilization. For instance, a double-normal distribution suggests that two populations (overgrazed and undergrazed areas) coexist in the same field, while a normal distribution suggests that there is no distinct grazing pattern. (Gibb and Ridout, 1986, 1988; Aiken et al., 1997). These are the most common definitions of biomass distribution of swards, but others exist that define non-normal distribution patterns (Barthram et al., 2005).

Estimating Biomass for Research Purposes

Difficulties with the direct harvesting methods have been well-established, but their precision make them irreplaceable in research studies when destructive sampling is not a concern (Gourley and McGowan , 1991; Harmoney et al., 1997; Sanderson et al., 2001; Tarr et al., 2005; Martin et al., 2005). When destructive sampling is considered unacceptable, researchers are limited to non-destructive methods such as the RPM. The RPM, which measures compressed sward surface height (CSSH), is often favored by grassland researchers because of its simplicity, low cost, ease of use, and the fast rate of sampling that can be achieved. Harmoney et al. (1997) reported that the RPM was extremely effective in estimating biomass of non-jointing cool season grasses, such as tall fescue ($R^2 = 0.85$) and Kentucky bluegrass ($R^2 = 0.58$); it is easy to use, and offered the most broad application in pastures with varying species when compared to the Robel pole, sward sticks, and a leaf canopy analyzer. Gourley and McGowan (1991) concluded that the RPM was an efficient research tool in measuring differences in biomass and noted that it reduced sampling time (4.5 h, 800 samples) when compared to direct harvesting (8.5h, 40 samples).

NDVI and Yield Estimates

NDVI, LAI, and Biomass

There is a strong linear correlation between the Leaf Area Index (LAI) and canopy biomass (Weiser et al., 1986; and Serrano et al., 2000), especially in tall fescue swards (R^2=0.96) (Trott et al., 1988). Because green vegetation and soil differ in their reflective properties in red and near infrared regions (NIR) of the electromagnetic spectrum, certain vegetative indices, such as the Normalized Difference Vegetation Index (NDVI), may be used to predict biomass at a low LAI (Serrano et al., 2000). The normalized difference vegetation index is defined as follows:

$$NDVI = \frac{NIR_{(780)} - red_{(660)}}{NIR_{(780)} + red_{(660)}}$$

According to Mitchell et al. (1990), red light reflectance may be as much as 10 times greater from soil as from vegetation, while NIR reflectance from vegetation may be twice that from soils. NDVI takes account of reflectance of both the canopy and the soil surface rather than just the canopy (Ma et al., 2001). Thus, NDVI may be used to estimate biomass of swards with LAI under 3.0 and less than 95% interception of light energy, situations that are common in grazed swards.

NDVI in Grain Crops

NDVI has become broadly researched as a tool for assessing above ground biomass and grain yield in many agronomic crops. Ma et al. (1996) found correlations between NDVI and maize grain yield ($R^2 = 0.50 - 0.80$) when NDVI was measured at anthesis. Ma et al. (2001) also reported correlations ($R^2 = 0.44 - 0.80$) between NDVI and soybean yields between growth stages R2-R5, with the higher correlation at the R5 stage. They concluded that NDVI could be used to estimate grain yield when the crop was in early reproductive stages. Correlations have also been reported for wheat ($R^2 = 0.83$) when NDVI measurements were made between Feekes 4 and 5 (Raun et al., 2001). Although good correlations have been recorded, grain yields are partly determined by environmental conditions during the reproductive stage of growth; therefore, above ground biomass is not an indicator of yield, but an indicator of the potential yield during these conditions.

NDVI in Grasslands

In grassland agriculture, where grazing and hay production are primary interests, above-ground biomass is an important variable. In grazing systems, NDVI and estimates of biomass derived from NDVI are indicators of pasture productivity. Both strong and moderate correlations have been found between NDVI and above ground biomass of shortgrass steepes ($R^2 = 0.66$) (Todd et al., 1998); alfalfa (*Medicago sativa*) ($R^2 = 0.89$) (Mitchell et al., 1990), and winter wheat (*Triticum aestivum*) ($R^2 = 0.60 - 0.78$) (Moges et al., 2004). NDVI has also been used to evaluate productivity for entire countries. In Mongolia, for example, NDVI derived from NOAA/AVHRR data have been used to evaluate pasture growth and to evaluate the long-term changes in pasture productivity over a 20 year period (Magsar, 2004). Overall, NDVI has proven to be an important variable in evaluating yield in many agronomic crops.

Factors Affecting the NDVI/Biomass Relationship

Soil Effects

Although the principles behind NDVI are quite simple, many factors are involved and affect its utility. Todd et al. (1998) stated that soil reflectance properties vary considerably with soil type, texture, moisture content, organic matter, color, and the presence of iron oxides. For instance, soils high in organic matter or high in moisture are darker and absorb more red and NIR radiation (Roderick et al., 2000). Although the biomass may be the same, these darker soils may return higher NDVI values than lighter colored soils. Therefore, varying soil conditions and soil types across a large landscape may make biomass more difficult to calculate from NDVI. This source of error in NDVI is minimized as LAI increases and less soil surface is exposed.

Dead Plant Material

The presence of dormant, senescent, decaying, and dead vegetation also interferes with NDVI and derived variables. The problem is expressed predominately in the absence of grazing, where dry vegetation and living green vegetation both coexist within a sward (Todd et al., 1998). In healthy green tissue NDVI values are higher because red light is absorbed by chlorophyll while NIR is reflected by the internal structures of leaves

(Roderick et al., 2000). In the absence of chlorophyll the opposite occurs and NDVI becomes a less effective tool because the reflectance patterns of the dead vegetation are more similar to that of soil than to healthy green vegetation (Todd et al., 1998). Differences in the reflective properties of the two groups tend to complicate remote sensing techniques, especially when calibrating a vegetative index.

Leaf Angle

Leaf angle and leaf distribution within a canopy also influence NDVI. Grasses, such as tall fescue, orchardgrass and bluegrass, have a spherical leaf distribution (leaves are distributed at random by angles of elevation and there azimuth angles), while legumes, such as red clover, white clover, and alfalfa, have a conical leaf distribution (leaves have a common angle of elevation but are random with respect to their azimuth angles) (Monteith, 1973). Due to these differing canopy architectures, most clovers tend to have less sunfleck (fractional area of sun that penetrates through the canopy) during solar noon and become light-saturated faster than grass species. Monteith (1973) measured these differences and reported an almost two-fold greater incidence of sunfleck in perennial ryegrass (*Lolium perenne* L.) (0.65) than in white clover (*Trifolium repens* L.) (0.33). Thus it is more difficult to predict biomass of swards that are light-saturated (Mutanga and Skidmore, 2004). We therefore have two situations that can coexist or exist independently in an ecosystem that make NDVI and biomass relationships difficult to define: light saturation problems due to canopy architecture and light saturation problems due to an increasing LAI over a plant growth cycle.

Variations in Soil Fertility

Leaf chlorophyll content is affected by plant available water and nitrogen in the root zone (Schlemmer et al., 2005), and spatial variation of these factors may cause variability in leaf chlorophyll content and subsequently NDVI. This is particularly noticeable in areas with a darker green color where urine and dung spots dot the landscape of a nitrogen-deficient grassland. Similar situations may exist in areas where erosion causes soil, water, and nitrogen to accumulate on foot and toeslopes and increase

the concentration of nutrients. Heckrath et al. (2005) concluded that erosion was a major contributor of within field variability of soil properties, mainly due to the concentration of nutrient-rich soil material in low-lying areas. Although tillage is rarely an issue in pastures, soil and nutrient deposition in low-lying areas may occur. This is especially true in pastures on steep terrain. Considering that a plant's photosynthetic potential is proportional to leaf chlorophyll content (Schlemmer et al., 2005), and that red light is readily absorbed by chlorophyll, one should take into consideration spatial variability of water, nitrogen and the terrain when examining sources of variation among NDVI measurements.

Greenseeker™

The Greenseeker™ was developed by Oklahoma State University engineers in an effort to utilize nitrogen-fertilization strategies for winter wheat that had been developed by OSU's soil scientists (http://nue.okstate.edu/). The Greenseeker™ uses multispectral active sensors to determine real time NDVI of crop canopies regardless of time of day or cloud cover. This NDVI database may be used to regulate the rate of application of aqueous nitrogen fertilizer according to predetermined production functions in the same operation or later as the database is GPS georeferenced.

Chapter 3

Site and botanical composition

   Two field experiments were conducted during this study. Experiment 1 was conducted at the Spindletop Research Farm (38°10' N, 84°49') in July and October 2004 on a 2.60 ha of endophyte-free (E-) tall fescue (*Festuca arundinacea* Schreb.) (cv Select) hay field. Experiment 2 was conducted at the University of Kentucky's Animal Research Center (ARC) (38°50' N, 84°44' W) in June 2005 on three 3.0 ha pastures of endophyte infected (E+) tall fescue (cv Kentucky 31) pastures. The pastures in Experiment 2 were being used for a grazing experiment on stocking rate effects on performance of steers grazing E+ tall fescue. The sward in Experiment 1 was primarily composed of E-tall fescue, but did contain a small percentage of other species such as nimblewill (*Muhlenbergia schreberi* J.F.), Kentucky bluegrass (*Poa pratensis* L.), and alfalfa (*Medicago sativa* L). Experiment 2 was primarily E+ tall fescue with a small percentage of Carolina horsenettle (*Solanum carolinense* L.)

Measuring canopy reflectance

   Canopy reflectance data was recorded by a Greenseeker® RT500 variable rate application and mapping system. The scanner has 8 sensors spaced 0.76 m apart on a 6.096 m boom. High intensity light emitting diodes (LED) pulse the canopy with red (660 nm) and NIR (780nm) radiation at high frequencies while a photodiode detector measures the reflected light. From the reflectance data, the Normalized Difference Vegetation Index (NDVI) is calculated and
averaged every 0.76 m by the onboard computer and stored on a compact flash card. The Greenseeker® system calculates NDVI as follows:

$$NDVI = \frac{NIR_{(780)} - red_{(660)}}{NIR_{(780)} - red_{(660)}}$$

Data on the compact flash card was processed using a Greenseeker® specific post-processing program that georeferences and stores data in a format suitable for GIS software analysis. For a more detailed description of this system and the sensor specifications, see http://nue.okstate.edu/.

<u>Biomass Estimation</u>

In Experiment 1, two different methods of correlating NDVI to biomass were compared. The two methods used were an indirect method using a semi-automated rising plate meter with a 24 cm x 24 cm, 630g aluminum plate and a direct method using a forage plot harvester. Methods were evaluated during two different periods of growth (July 14 - 29, and October7[th]- November 7th) so that the destructive method would not interfere with the non-destructive method.

Rising Plate Meter

The RPM was used during the July portion of this experiment because of its linear relationship with sward biomass (Harmoney et al., 1997) and because of the speed at which samples could be taken (Gourley and McGowan, 1991). The RPM also allowed repeated estimates of sward biomass over a period of time with minimal sward disturbance. Calibrating the RPM was achieved by taking five measurements along a transect (2 by 0.41 m (0.82 m^2)), and then harvesting the biomass along that transect. Herbage within transects were cut to the soil surface with a Stihl® HS 80 hedge trimmer, then herbage samples were oven-dried to a constant weight at 80°C and weighed. Measurements of biomass were regressed against the average CSSH for each transect and the regression equation was used to estimate biomass from CSSH data.

Direct Harvesting

Direct harvesting was chosen as the second method of biomass estimation due to the accuracy at which samples can be taken (Gourley and McGowan , 1991; Harmoney et al., 1997; Sanderson et al., 2001; Tarr et al., 2005; Martin et al., 2005). The Hege 212 Forage plot harvester® (Wintersteiger Inc., Salt Lake City UT) was used to harvest biomass, because it allowed for measurements to be taken quickly, compared to traditional hand clipped quadrat methods of harvesting. Twelve swards (6 x 6 m) were cut to 5 cm and weighed. Grab samples from each sward were dried to a constant weight at 80°C to estimate the dry matter of the harvested area

GPS-enabled Rising Plate Meter

A GPS-enabled RPM was used in Experiment 2. The GPS-enabled RPM had a 43 x 43 cm, 1925 g aluminum plate and was integrated with a Bluetooth-enabled HP Pocket PC, an AgGPS® 132 DGPS Receiver, and a Bluetooth-enabled Leica DISTO® laser distance meter (Leica Geosystems, Norcross, GA). The Leica DISTO® plus was accurate to 1.5 mm and was operated in a continuous measurement mode. The distancemeter was mounted 1.25 m on the pole of the RPM and logged CSSH when the operator initiated the "Enter" command on the distancemeter keypad. Once the data was recorded by the distancemeter it was transferred via Bluetooth to the pocket PC where ArcPad 6.0 (ESRI® ArcPad 6, 2003) logged the CSSH and the coordinates where the measurement was taken.   The GPS-enable RPM was calibrated against herbage mass (> 50 mm) in 43 x 43 cm quadrats. Herbage samples were dried and weighed as previously described and the relationship between CSSH and biomass was determined by linear regression.

Experiment 1

During Experiment 1, NDVI data was collected with the Greenseeker® each week for 3 weeks throughout the month of July. A sampling grid (22.86 x 22.86 m) consisting of 50 points was used to relate biomass and NDVI data. Ten random RPM measurements were taken within 9 m of each point to estimate the average compressed sward height. Biomass at each grid intersection was estimated from an algorithm developed during the calibration of the RPM.

NDVI data was downloaded and processed in ArcMap 9.0. (ESRI® ArcMap 9.0., 2004) as well as grid points used in sampling and estimates of biomass at grid intersections. Buffers, 22.86 m in diameter, were created around each grid intersection with the Buffering Wizard tool in ArcMap. Each buffer was assigned the average sward height data collected for that area, the GPS coordinate of the buffer center, and the average of all the NDVI data points within the buffer. Average biomass was regressed against the average NDVI for each buffer.

In October 2004, a second method was used to define the relationship between NDVI and biomass of tall fescue. Twelve random 6 x 6 m (36 m^2) plots were scanned

with the Greenseeker® to determine the NDVI each week for 3 weeks and cut to 5 cm stubble height to determine biomass. As before, biomass estimates were regressed against the average NDVI values for each plot.

Experiment 2

The second experiment was conducted on a beef stocker grazing experiment with five stocking rates (2.3, 4.3, 6.3, 8.3, and 10.7 head ha^{-1}) on Kentucky 31+ tall fescue pastures. Out of the ten pastures used in this experiment, three (4.3, 6.3, and 8.3 head ha^{-1}) were chosen to represent light (1226 kg BW ha^{-1}), intermediate (1780 kg BW ha^{-1}), and heavy (2344 kg BW ha^{-1}) stocking rates, respectively. Each pasture was mapped on day 56 of the 63 day study using the Greenseeker® in the same manner as in Experiment 1. Cattle during this time frame had a slight, insignificant reduction in body weight due to the effects of fescue toxicosis and therefore the stocking rate stayed relatively constant over the 56 day period. To determine if NDVI values calculated and recorded by the Greenseeker® were spatially structured for the use of yield mapping within pastures, variogram models were constructed and analyzed (Nielsen and Wendroth, 2003).

To calibrate NDVI approximately 20 CSSH measurements were collected across each of 3 transect within each field, for a total of 60 samples per field. CSSH measurements were taken using the GPS-enabled RPM, and data from both the Greenseeker® and the RPM were downloaded to ArcMap 9.0 (ESRI® ArcMap 9.0., 2004) for analysis. Buffers were created around each point taken by the RPM and assigned coordinates, a CSSH, and the average of all the NDVI data points within the buffer. Optimum buffer size was determined by the analysis of linear regression models, in which buffers ranging from 0.5 to 4.0m in 0.5m increments were compared based on correlation coefficients and mean absolute error. Further analysis was conducted through the use of spatial coregionalization models (Nielsen and Wendroth, 2003), in which cokriged values of CSSH measurements for differing buffer sizes were compared by their mean absolute error (error$_{abs}$).

Histograms of DM estimates derived from NDVI maps were used for the analysis of each field to determine the pasture condition and the efficiency of the stocking rate. Guidelines for forage availability (kg DM ha^{-1}) were set at levels specified by Dougherty

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and Collins (2003).   Each field was evaluated based on mean yield, mean yield above 1680 kg ha^{-1}, and skewness and kurtosis of its histogram.

<u>Statistics</u>

Regression models for NDVI and CSSH were calculated using the Proc Reg procedure in SAS (SAS Institute Inc., 2003). Spatial analysis of NDVI and CSSH were conducted using GS^{+} software (GS^{+}, 2005). When NDVI and CSSH were used in cokriging, CSSH was the primary variate with NDVI being the covariate. Semivariograms and crossvariograms created for cokriging were primarily fitted with exponential or Gaussian variogram models. Models are defined as:

Exponential:

$$\gamma(h) = C_O + C[1 - \exp(-h/A_O)]$$

Gaussian:

$$\gamma(h) = C_O + C[1 - \exp(-h/A_O)^2]$$

where h = lag distance, C_O = nugget variance ≥ 0, C = structural variance ≥ 0 and A_O = range parameter. When regression and cokriging were compared, the mean absolute error was used as a measure of precision. The mean absolute error was calculated according to:

$$\text{error}_{abs} = \sum_{i=1}^{n} \frac{|x_i - \hat{x}_i|}{n-1}$$

where x_i is the measured value of CSSH, $\hat{x}_i$ the predicted value, and n is the number of samples. Histograms were presented and analyzed using ArcMap 9.0 (ESRI$^{®}$ ArcMap 9.0., 2004), with class intervals set at increments of 100 (e.g. 100-199 kg). Skewness and kurtosis were calculated as follows:

Skewness:

$$\gamma_{skewness} = \frac{\mu_3}{\mu_2^{3/2}}$$

Kurtosis

$$\gamma_{kurtosis} = \frac{\mu_4}{\mu_2^{2}}$$

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The moment of order k (μ_k) is defined as:

$$\mu_k = \frac{1}{n} \sum_{i=1}^{n} \left(z_i - \bar{z} \right)^k$$

where n = sample size, z_i = the sample element, $\bar{z}$ = sample mean, i = is the moment, and k = the order.

Chapter 4

Weather

In 2004 and 2005 extremes in precipitation were recorded for the Commonwealth of Kentucky (http://wwwagwx.ca.uky.edu/cgi-public/farm_www.ehtml): 2004 being one of the wettest years on record with 142 cm of precipitation, and 2005 being one of the driest with 94 cm (124 cm norm). During 2004 Spindletop Farm (Experiment 1) reported 133 cm of rainfall, of which 100 cm was received during the growing season (March 15 - November 15) (Figure. 1a). The following year (2005), ARC (Experiment 2) reported only 69 cm of rainfall with only 46 cm being received during the growing season (Figure. 1b).

Soils

The field used in Experiment 1 covered 2.60 ha, of which 78% was composed of a Maury silt loam (MiB) and 22% a Lanton silty clay loam (dunning) (La) (Figure. 2a). Experiment 2 consisted of three 3.0 ha fields: Field 1 (Figure. 2b) consisted of 63% Donerail silt loam (Dob), 15% MiB, and 22% Maury silt loam (MiC); Field 2 (Figure. 2c) was composed of 17% Dob, 48% MiB, 2% MiC, and 33% McAfee silt loam (MnC); and Field 3 (Figure. 2d) consisted of 1% DoB, 4% Huntington silt loam (Hu), 48% LwB, 37% Lowell silt loam (LwC) and 10% MiB (NRCS, 2005).

Experiment 1

Calibration of RPM and NDVI

Regression of CSSH taken with the RPM over three sampling dates was highly correlated with biomass (y = 233.6x - 382.5; P = 0.02; n = 24; R^2 = 0.89) (Figure. 3) and allowed for quick data collection. Because of its high correlation with biomass, 10 CSSH measurements were taken and averaged within each buffer (22.8 m diameter) for the 50 predetermined points and then regressed against average NDVI values recorded within each buffer. Regressions of data pooled over the three week sampling period (y = 54.1x - 34.1; n = 150; R^2 = 0.54; P = 0.0001) (Figure. 4) supported the use of NDVI to estimate biomass. When data was sorted by date of sampling (July 14th, 21st, and 29th), correlations

were poorer than that of pooled data, but they indicated that linear correlations increased with the date of sampling ($R^2 = 0.10 - 0.31 - 0.43$ respectively) (Figure. 5).

Cokriging of Buffer Data

In an effort to improve estimates of CSSH by taking into account spatial correlations between sampled points, further analysis of data was conducted by cokriging. When the mean absolute error of cokriged estimates was compared to that of the linear regression models, only the first sampling date favored cokriging as the estimation method ($error_{abs} = 0.54$ compared to 0.58) (Table 1).

Calibration of NDVI using Direct Harvesting

Linear regression ($y = 743.58x - 369.53$; $P = 0.0001$; $n = 36$; $R^2 = 0.68$) between estimates of biomass determined with the forage plot harvester and NDVI (pooled over the 3 week sampling period) (Figure. 6) was more precise than the regression for biomass estimated by the RPM method (Figure. 3). When stratified by sample date (October 7th, 22nd, and November 7th), the correlation coefficients of the regression models for the 2.0m buffer data were again less powerful than the pooled data, but showed an opposite trend in which the linear correlation decreased with the date of sampling ($R^2 = 0.62$, 0.47, and 0.27, respectively) (Figure. 7). Cokriging of yield and NDVI data was not conducted within these areas due to the limited number of samples taken at each sampling date.

Experiment 2

Adequacy of NDVI Sampling

Semivariograms were used to determine if sampling at a 0.76 m distance with the Greenseeker[®] provided information about the spatial variability structure. Isotropic variograms were calculated from the approximately 56,000 NDVI data points recorded for each field and then fitted with an appropriate variogram model type. The exponential model provided the best fit to semivariogram data for all fields, and all models were similar with respect to the nugget, sill, and range parameters. However, these parameters still highlighted key differences in spatial variability between swards by identifying the

extent of small scale variability incurred with each SR (Figure. 8). Model parameters can be viewed in Table 2.

Calibration of RPM and NDVI

Due to the extensive scale of each field and the need to nondestructively estimate biomass, the RPM was chosen as the method by which NDVI data would be calibrated. Unlike Experiment 1, where a standard RPM was used, a new GPS enabled RPM, that not only recorded data but also georeferenced and logged measurements individually, was used to collect biomass information. Calibration of the GPS enabled RPM, derived from pooled samples, was correlated (y = 231.68x - 57.67; P = 0.0001; n = 19, R^2 = 0.69) with biomass and supported the use of the RPM as the calibration method (Figure 9). To calibrate NDVI for the estimation of biomass, approximately 50-60 CSSH measurements were recorded and mapped along 3 transects within each field and then overlaid on NDVI maps using ESRI ArcMap Software (ESRI ArcMap 9.0, 2004). Each measurement was logged and georeferenced individually and assigned a series of buffers ranging from 0.5 to 4.0 m in 0.5 m increments in ArcMap to identify an optimum buffer size for the regression model. The average NDVI value obtained from each buffer size at a respective location was regressed against the corresponding CSSH. The largest correlation was obtained for an optimum buffer size of 2 m (Table 3) (y = 44.61x - 21.26; P = 0.0001; n = 180; R = 0.44) for pooled data (Figure. 10). Quadratic models were not considered because of their tendency to overestimate extremely low NDVI values and their inability to estimate a minimum NDVI at which biomass would be present.

Cokriging of Buffer Data

When cokriging was applied to these same buffer data sets, mean absolute errors of cokriged estimates of CSSH showed similar values, and therefore could not be used to identify an optimum buffer size (Table 3). By using these procedures to compare mean absolute errors of regression and cokriging models for the 2.0 m buffer size, it was determined that cokriging estimates ($error_{abs}$ = 2.23) had a slight advantage over classical linear regression estimates ($error_{abs}$ = 2.28).

Optimum Buffer Size for Individual Fields

Analysis of individual field data revealed differing optimum buffer sizes (Table 4) with Field 1 (light SR) showing the strongest correlation at 3.0 m (y = 82.29x - 49.54; P = 0.0001; n = 69; R^2 = 0.23), Field 2 (intermediate SR) at 0.5m (y = 12.59x + 2.67; P = 0.11; n = 58; R^2 = 0.04), and Field 3 (heavy SR) at 2.0 m (y = 21.87x – 7.87; P = 0.0003; N = 53; R^2 = 0.23) (Figure. 11). When cokriging was applied to these optimum buffer sizes for individual fields and the mean absolute errors compared to those from regression models, cokriging models produced inferior results (Table 5). Although cokriging applied to buffer data did offer a slight improvement in the mean absolute error in some situations, it could not be used to interpolate the raw NDVI data sets from CSSH because spatial co-regionalization models failed to meet the conditions needed to ensure "positive definiteness" (Nielsen and Wendroth, 2003). Therefore NDVI data points were converted to DM estimates based on linear regression models.

Estimating Biomass and Guidelines for Animal Intake

By using the linear regression model derived from the pooled 2 m buffer data, NDVI values were converted to DM estimates for all mapped NDVI data points. For the purpose of simplicity, points were given DM values based on the kg ha^{-1} instead of kg 0.58m^{-2} (area of individual NDVI points). Biomass at NDVI values below 0.48 were set at 0 kg DM ha^{-1} to eliminate negative values estimated by this regression model, and guidelines for forage availability and its effect on ruminant intake were set as follows: inaccessible < 840 kg DM ha^{-1}(unable to graze), restricted 840 – 1680 kg DM ha^{-1} (grazing but with bite size below optimum), and non-restricted > 1680 kg DM ha^{-1} (grazing with bite size optimized) (Dougherty and Collins, 2003). Presenting each data point in kg DM ha^{-1} and setting guidelines for forage availability based on kg DM ha^{-1} allowed for conventional analysis of yield data and evaluation of forage availability at specified locations.

Histogram Analysis

Evaluation of histograms based on DM estimates for Fields 1 (light SR) and 2 (intermediate SR) showed frequency distributions to be negatively skewed (-0.97 and -

0.62, respectively), with kurtosis (4.75 and 3.5, respectively) above normal (3.0) (Figure. 12). However Field 3 (heavy SR) was positively skewed (0.27) and exhibited a below normal kurtosis (2.75). These differences in skewness and kurtosis between fields indicated different levels of forage consumption and differences in grazing behavior between fields. Further analysis of histograms indicated that Field 1 (light SR) had a mean yield of 2,693 kg DM ha^{-1} (s = 532) with DM estimates ranging from 0 to 4,218 kg DM ha^{-1}. Of those yield estimates, 95 percent were above 1,680 kg DM ha^{-1}, which was defined by the adopted guidelines as the minimum level of non-restricted intake (MLNI). Field 2 (intermediate SR) had a mean of 2,370 kg DM ha^{-1} (s = 618), showed a similar range of DM estimates (0 – 4,105 kg DM ha^{-1}) and had 86 percent of yield estimates above MLNI. Field 3 (heavy SR), however, had a much lower mean yield of 1,576 kg DM ha^{-1} (s = 627) with only 41 percent of the observation lying above MLNI but did have a similar range of yield values (0 – 3,923 kg DM ha^{-1}). While the mean is normally used to gauge field condition, the amount of DM above MLNI is more insightful in evaluating forage availability (Figure. 13). This is because animals preferentially graze areas of forage that optimize intake and do not graze areas below MLNI unless forced to by the contamination of dung in the higher yielding areas of the sward or if no other options exist (Aiken et al., 1997). Therefore, only histogram data above MLNI will be used to determine the condition of these grazing systems. When just the ranges of values above MLNI were analyzed Field 1 (light SR) showed a mean yield of 2,763 kg DM ha^{-1}(s = 430), Field 2 (intermediate SR) a mean of 2,539 kg DM ha^{-1} (s = 449), and Field 3 (heavy SR) a mean of 2,182 kg DM ha^{-1} (s = 383). One must keep in mind that these values only represent the areas of the field that have forage above MLNI and do not represent the average biomass over the entire field. These values can now be used to determine the amount of forage that is available for consumption before intake will be restricted. Based on these mean values, the amount of available forage above MLNI can be calculated as follows:

Available Forage$_{MLNI}$ = (percentage DM above MLNI x total area) x (mean above MLNI -1,680)

By applying this equation it is estimated that Fields 1, 2, and 3 have a total of 3,087 kg, 2216 kg (DM), and 617 kg (DM) respectively of forage available above MLNI. When animal intake and areas of fecal contamination are considered, these estimates may also be used to estimate grazing days left within each field.

Tables

Table 1. Comparison of statistical methods by which CSSH could be
estimated from NDVI. Comparison were made by observing the mean
absolute errors associated with each method (stratified by sampling date)
(Experiment 2).

	$Error_{abs}$ Regression Model	$Error_{abs}$ Cokriging
07/16/04	0.58	0.54
07/21/04	0.51	0.62
07/29/04	0.70	0.72

Table 2. Parameters of the exponential models used to describe the semivariograms
of each SR (Experiment 2).

	Model Type	Nugget (c_o)	Sill ($C + c_o$)	Range (A_o)
Light SR	Exponential	0.001364	0.003908	2.56
Intermediate SR	Exponential	0.001359	0.003947	1.83
High SR	Exponential	0.001491	0.003270	1.33

Table 3. Comparison of buffers using regression and cokriging. Buffer were
compared to identify which buffer size should be used in estimating dry matter
from NDVI. Optimum buffer size was determined by identify the best correlation
coefficient (regression of NDVI against CSSH) among buffer sizes. A second
comparison was also made using the mean absolute errors of cokriged estimates
for each buffer size. Cokriging provided little information on the optimum buffer
size (Experiment 2).

	Buffer Diameter							
	0.5m	1.0m	1.5	2.0m	2.5m	3.0m	3.5m	4.0m
Regression (R^2)	0.31	0.35	0.40	0.44	0.43	0.42	0.40	0.40
Cokriging ($Error_{abs}$)	2.23	2.23	2.23	2.23	2.24	2.24	2.24	2.24

Table 4. Identifying the optimum buffer size for the light SR, intermediate SR, and heavy SR. Optimum buffer size was determined by identify the best correlation coefficient (regression of NDVI against CSSH) among buffer sizes for individual stocking rates (Experiment 2).

	Buffer Diameter							
	0.5m	1.0m	1.5m	2.0m	2.5m	3.0m	3.5m	4.0m
Light SR	0.005	0.07	0.15	0.22	0.22	0.23	0.19	0.17
Intermediate Sr	0.04	0.002	0.01	0.01	0.02	0.01	0.004	0.0007
Heavy SR	0.16	0.21	0.21	0.23	0.21	0.21	0.21	0.22

Table 5. Comparison of mean absolute errors of regression and cokriging estimates to identify the best statistical method by which CSSH could be estimated from NDVI buffer data (Experiment 2).

	$Error_{abs}$ (Regression)	$Error_{abs}$ (cokriging)
Light SR	2.46	2.55
Intermediate SR	2.19	2.44
Heavy SR	1.17	1.62
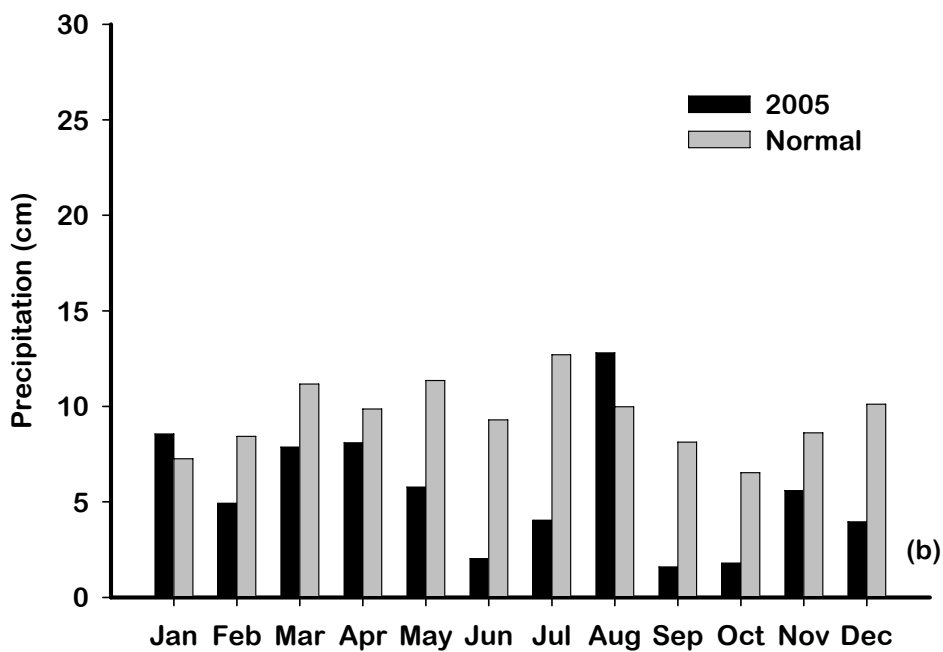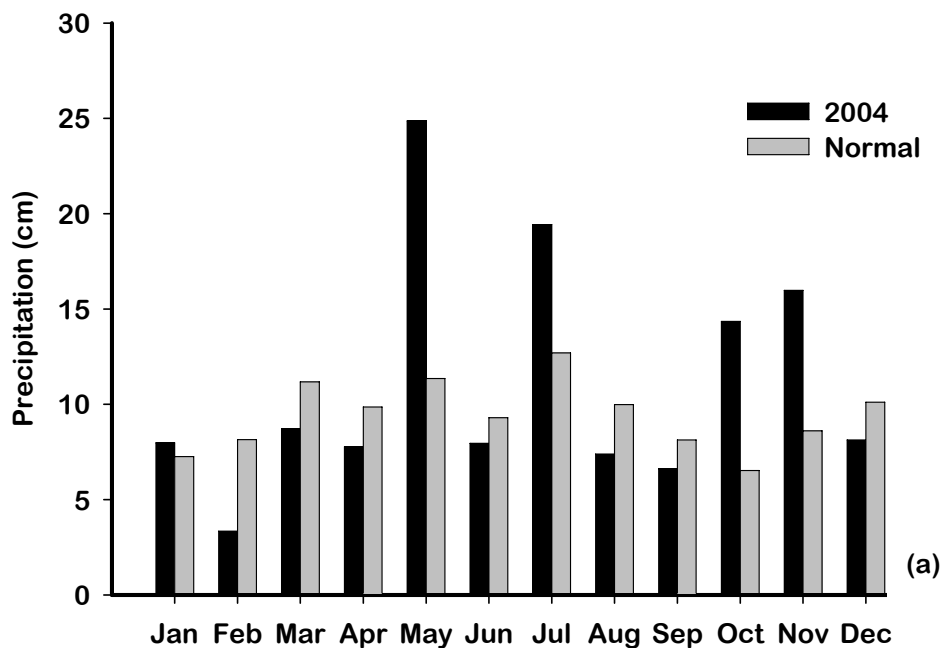
Figure 1. Monthly rainfall data collected during Experiment 1 (a) and Experiment 2 (b) at their respective sites.
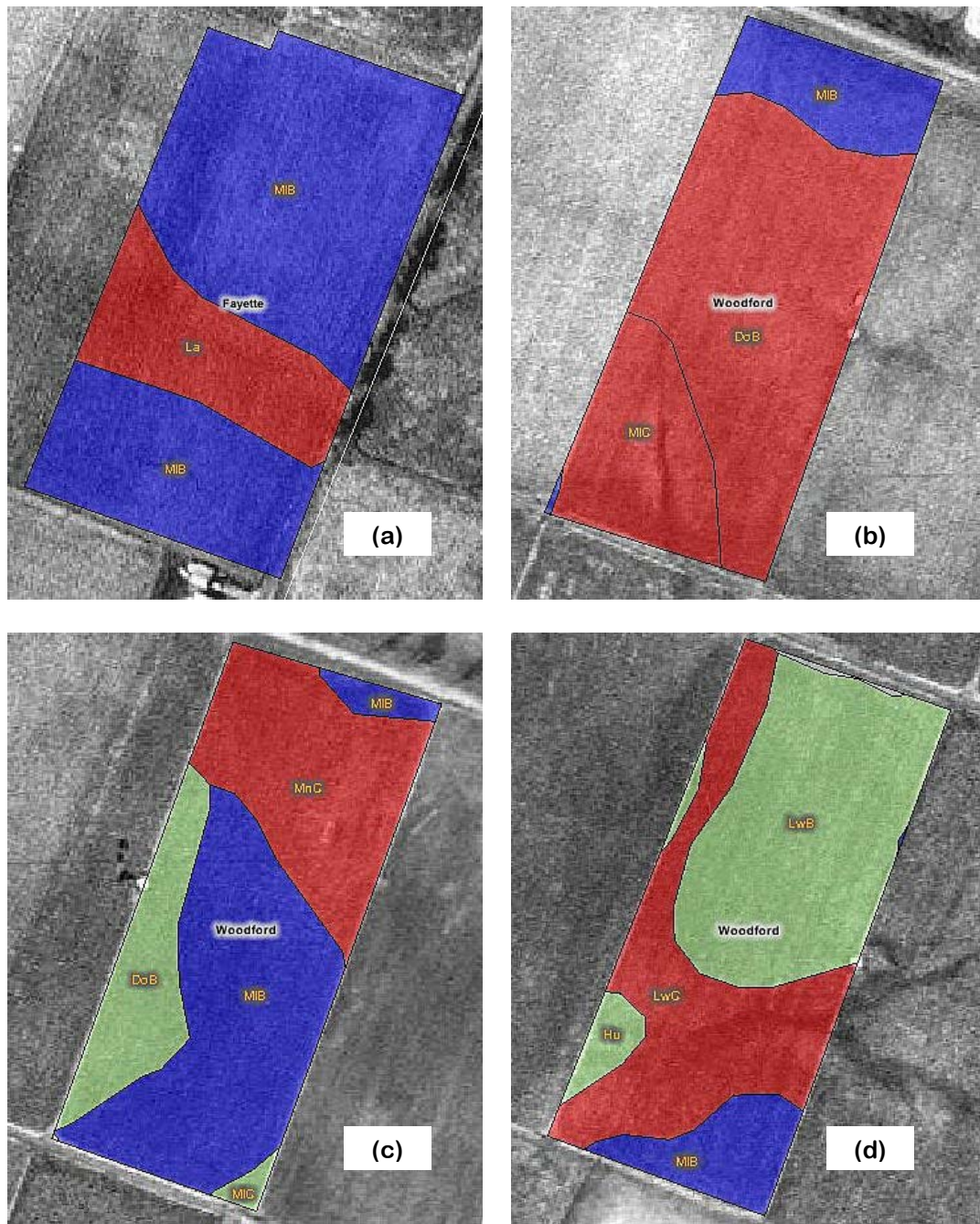
Figure 2. Soil maps of the fields used in Experiment 1 and 2: (a) Experiment 1; (b-d) Fields 1-3 (respectively) of Experiment 2. Soil abbreviations; Maury silt loam (MiB and MiC), Lanton silty clay loam (dunning) (La), Donerail silt Loam (DoB), McAfee silt loam (MnC), Huntington silt loam (Hu), and Lowell silt loam (LwB and LwC).
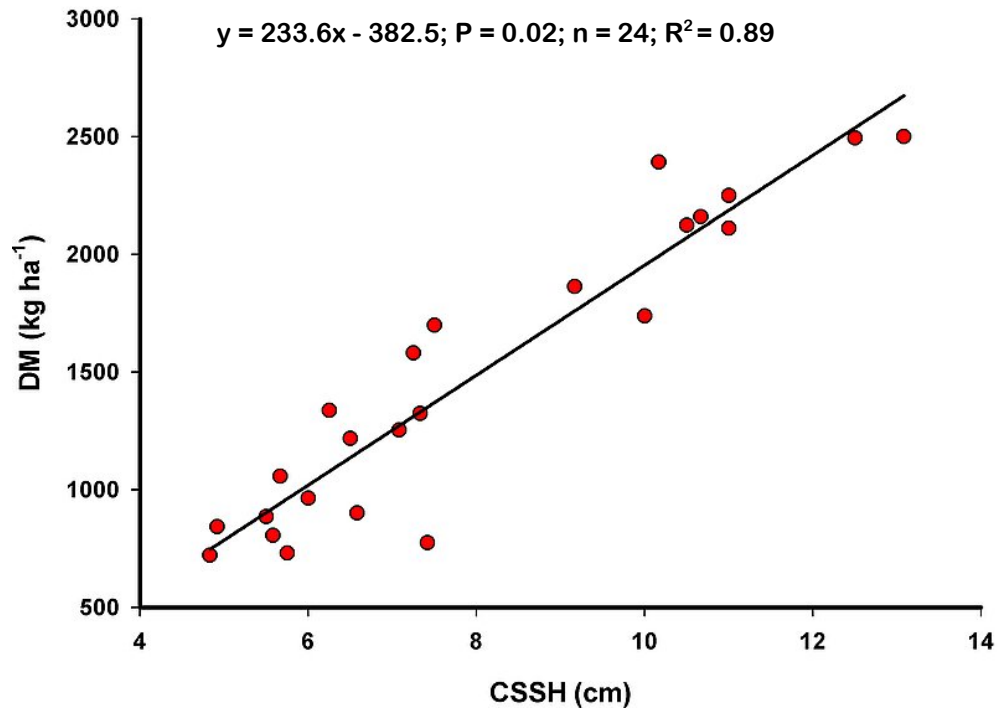
Figure 3. Regression of CSSH against DM in Experiment 1.
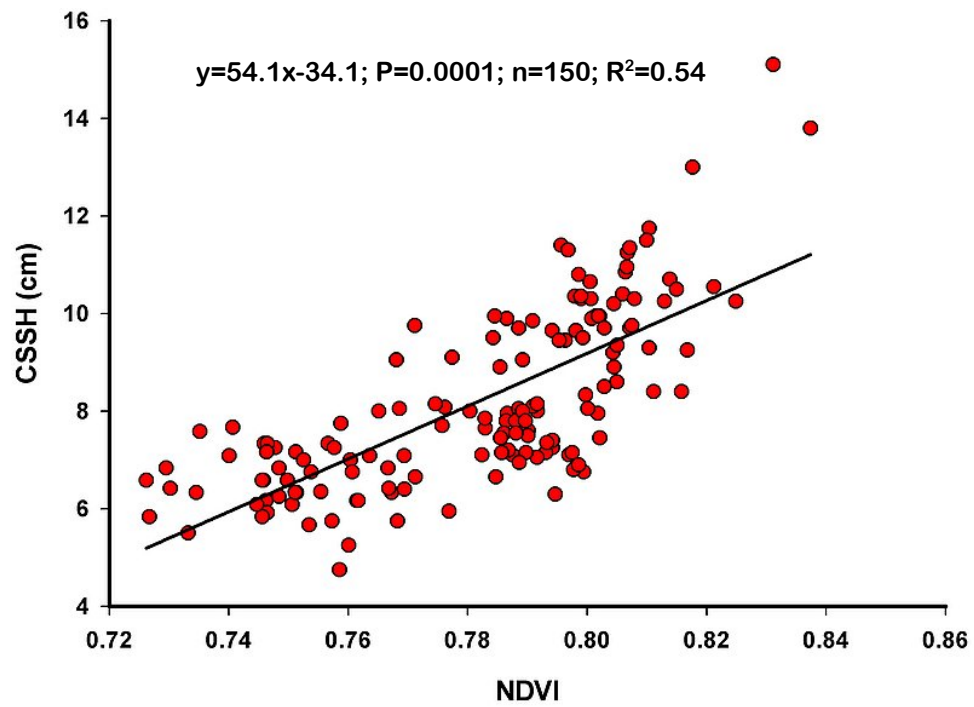
Figure 4. Regression of NDVI against CSSH in Experiment 1.
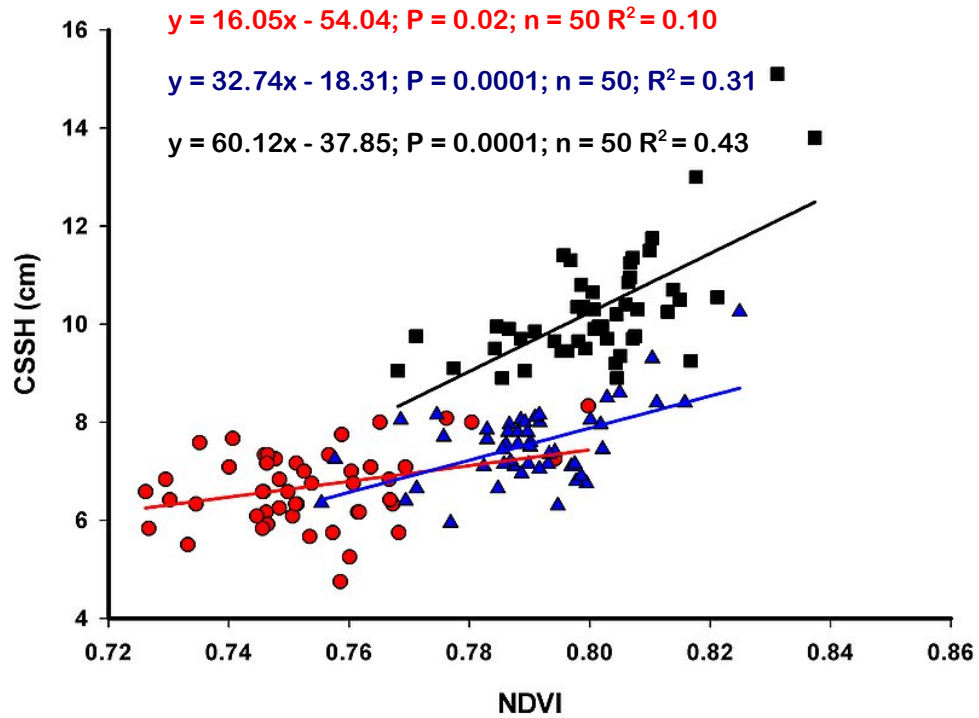
Figure 5. Regression of CSSH against NDVI (stratified by sampling date): (●) 07-14-04; (▲) 07-20-04; (■) 07-29-04. Correlation coefficients show an increasing trend with date of sampling.
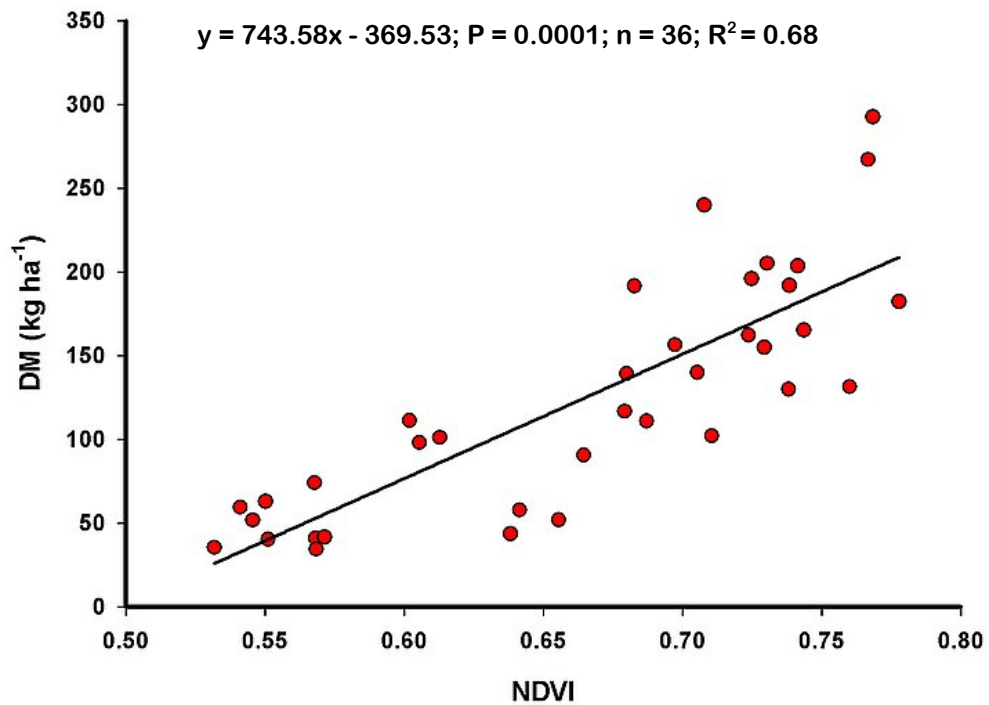
Figure 6. Regression of NDVI against DM (kg ha[-1]) using the direct harvesting method to sample biomass.
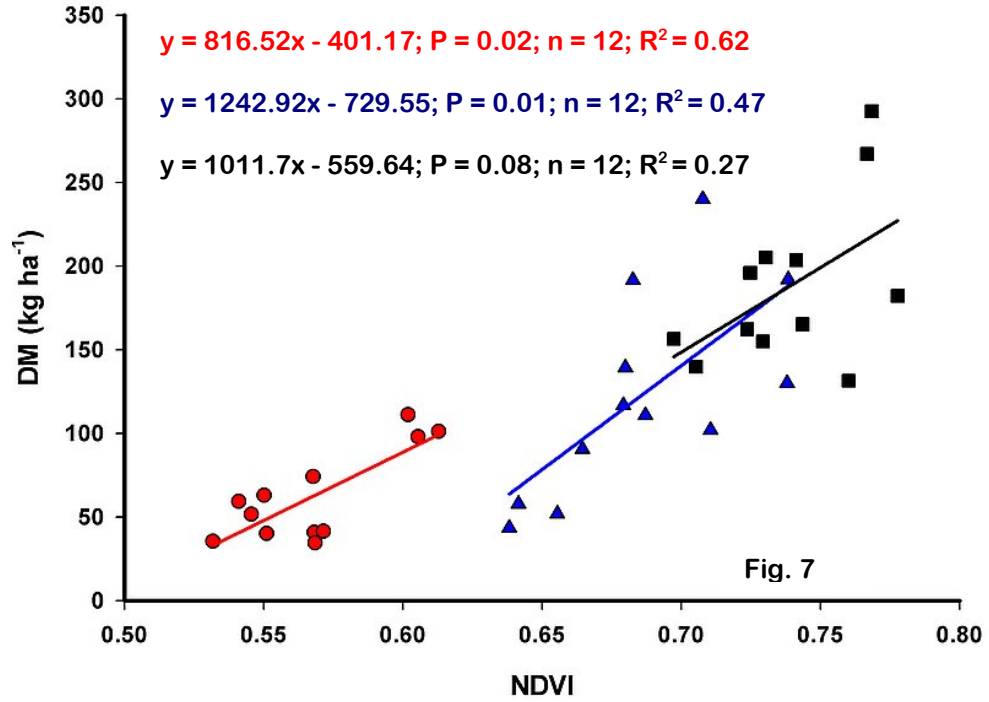
Figure 7. Relationship between NDVI and biomass estimated by the direct harvesting method, stratified by sampling date (Experiment 2): (●) 10-07-04; (▲) 10-22-04; (■) 11-07-04. Correlation coefficients show a decreasing trend with date of sampling.
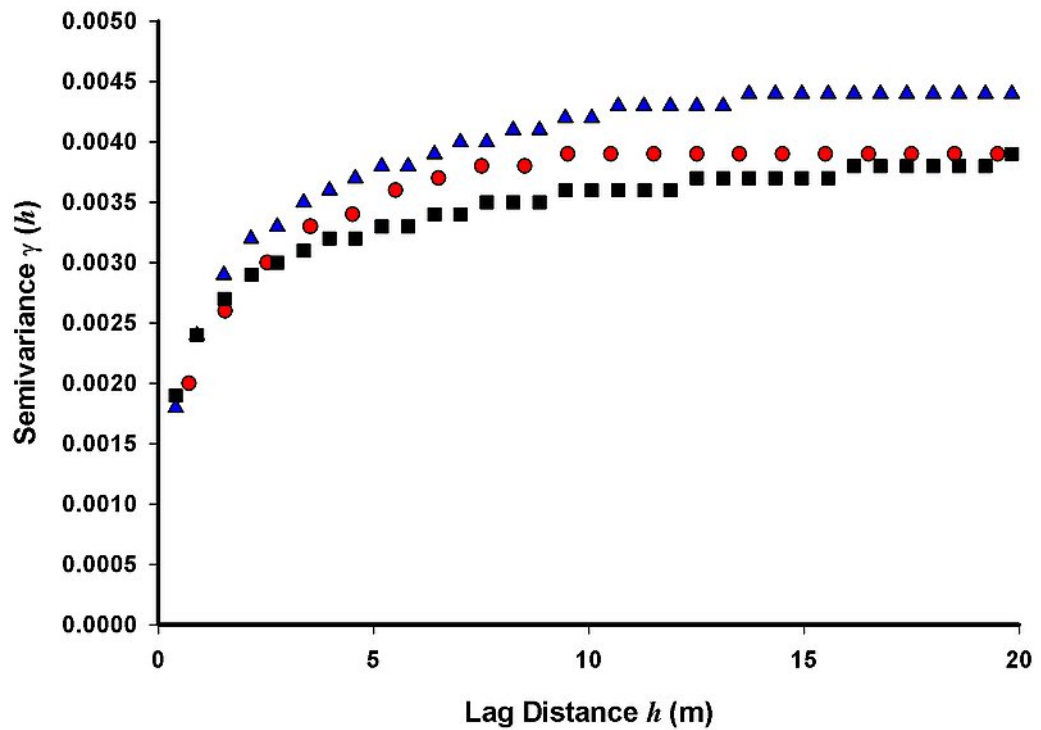
Figure 8. Semivariograms of Experiment 2 fields; (●) light SR, (▲) intermediate SR, and (■) heavy SR.
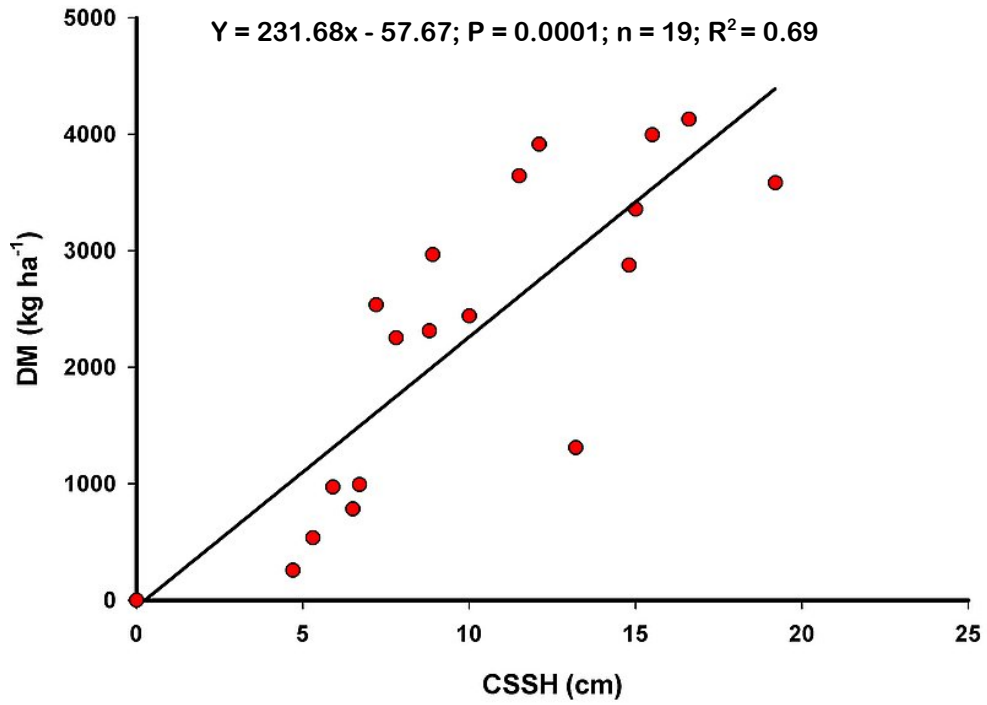
Figure 9. Relationship between CSSH and DM (kg ha^{-1}) in Experiment 2. Data collected was used to calibrate the rising plate meter.
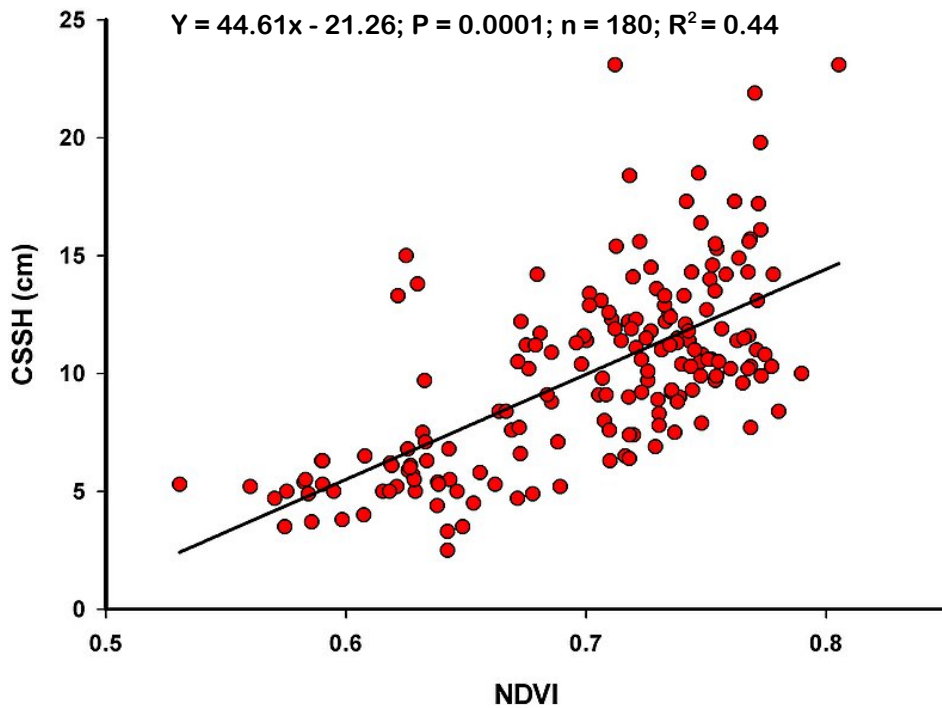
Figure 10. Relationship between NDVI and CSSH (cm) of all 3 fields using a 2.0m buffer diameter.
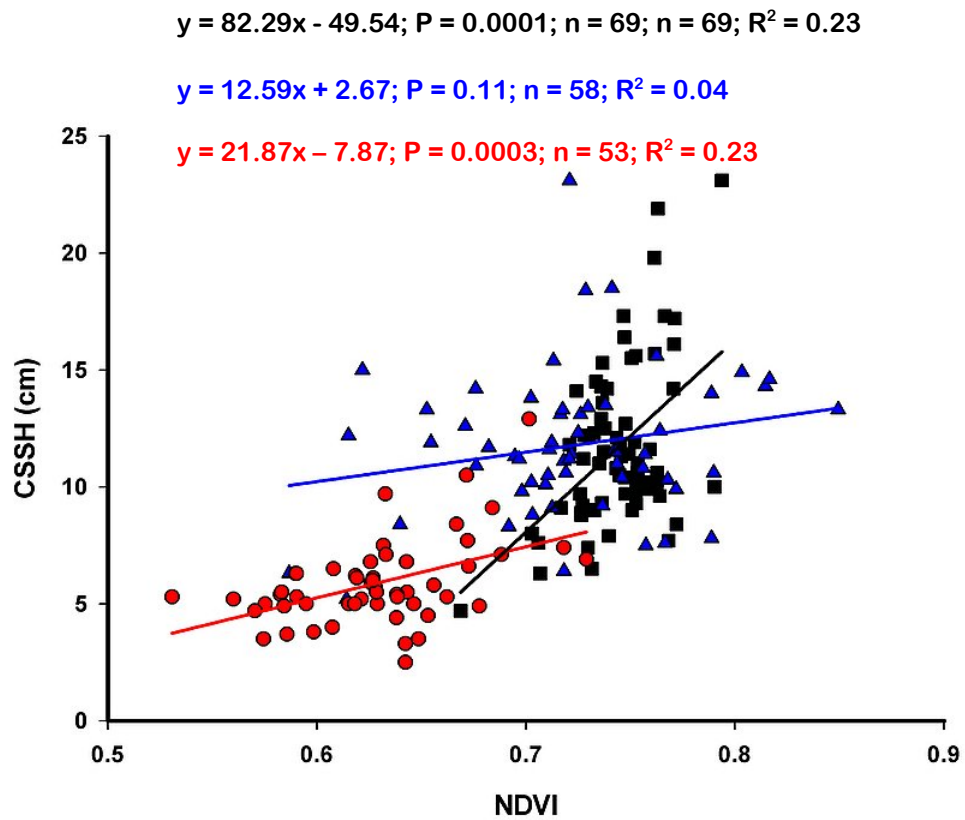
Figure 11. Relationship between NDVI and biomass of individual fields: (●) light SR; (▲) intermediate SR; (■) heavy SR.

$y = 82.29x - 49.54$; $P = 0.0001$; $n = 69$; $n = 69$; $R^2 = 0.23$

$y = 12.59x + 2.67$; $P = 0.11$; $n = 58$; $R^2 = 0.04$

$y = 21.87x - 7.87$; $P = 0.0003$; $n = 53$; $R^2 = 0.23$
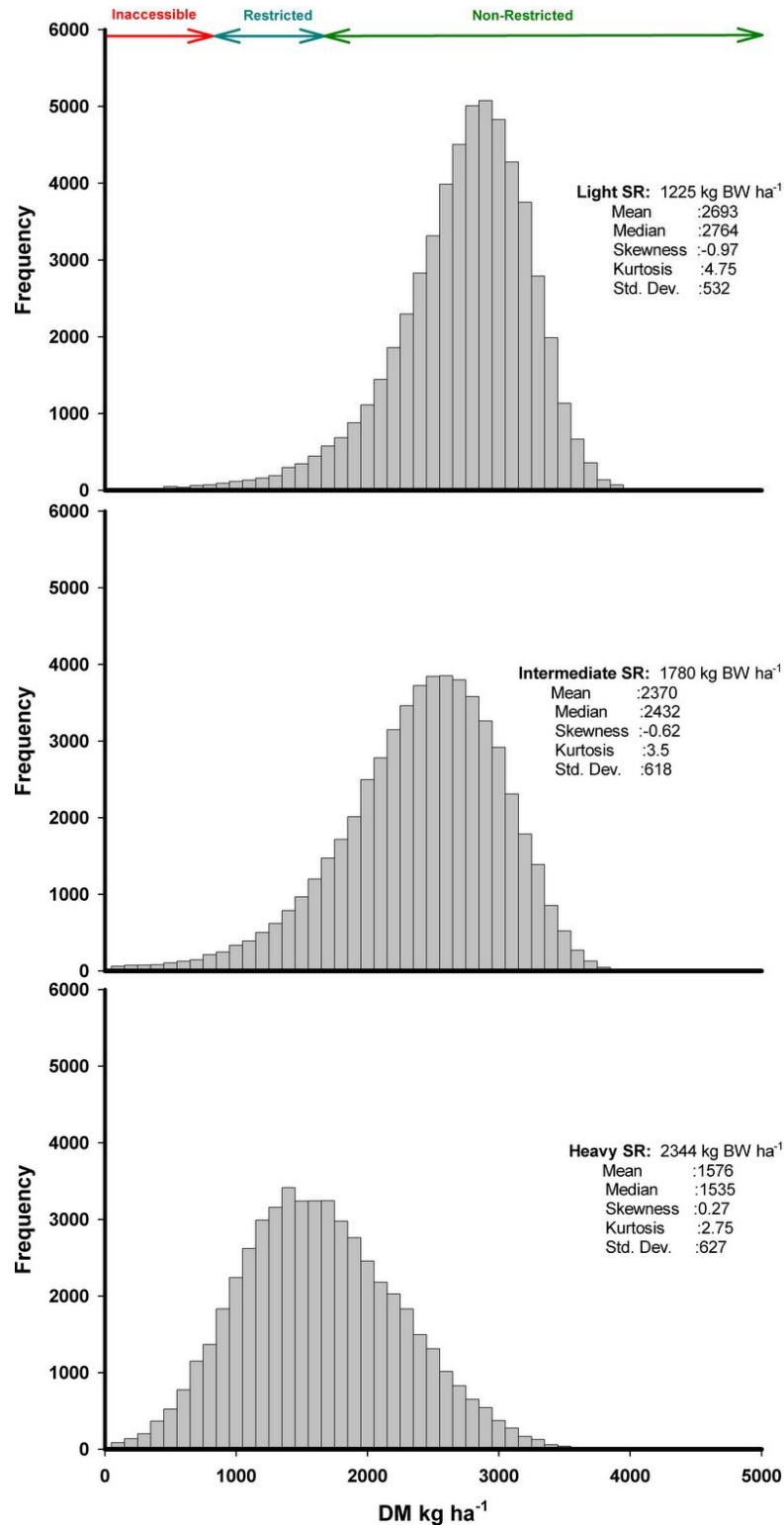
Figure 12. Histograms of field biomass for three stocking rates. Biomass estimates derived from NDVI data were calculated using linear regression models from Figures 9 and 10. Each histogram was created using approximately 56,000 individual NDVI data points.
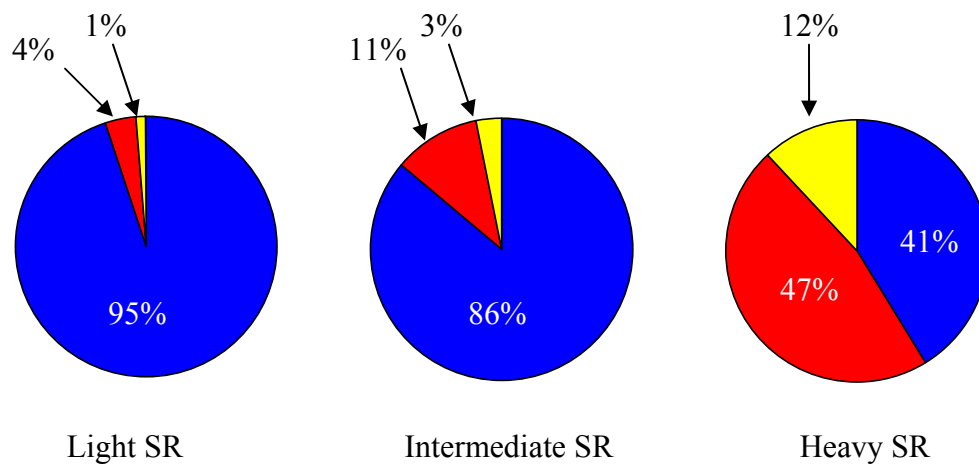
Figure 13. Grazed fields broken down by percentage of forage availability: inaccessible (yellow), restricted (red), and Non-restricted (blue).

Chapter 5

<u>Experiment 1</u>

Adequacy of Calibration Methods

  The higher correlation coefficient for the regression of NDVI against biomass using the direct harvesting method was expected due to the accuracy of direct measurements (Gourley and McGowan , 1991; Harmoney et al., 1997; Sanderson et al., 2001; Tarr et al., 2005; and Martin et al., 2005) and because NDVI measurement were only recorded for the areas to be harvested. This eliminated much of the sampling error associated with biomass sampling and prevented GPS inaccuracies (Trimble Navigation Limited, 1999) from mismatching biomass data and NDVI values. However direct harvesting was not as time efficient (3 hr) for the 12 points sampled as it was for the 50 points sampled by the RPM (1.5-2 hr) (Gourley and McGowan, 1991), nor did it account for as much spatial variability as the RPM method. Regardless, results indicate that either method may be used to estimate biomass from NDVI.

Sampling Date Trends

  Different trends in correlation coefficients observed for each calibration method may be due to the time of year in which data was collected and the different heights at which each sample method was cut or calibrated. In July biomass grew vigorously. Canopy height was uniform in the beginning due to mechanical harvesting, but became increasingly spatially heterogeneous over time probably as a result of spatial variations in soil fertility and availability of soil water (Heckrath et al., 2005). This resulted in a wide range of yield estimates (727 – 3144 kg/ha), over a short range of NDVI values (0.73 – 0 .84). In October the canopy height again started out uniform but appeared to have less canopy cover in certain areas as indicated by a minimum NDVI value of 0.53. When these sward conditions were combined with poor growth, a narrow range of yield estimates (34 – 293 kg/ha) was observed over a relatively wide range of NDVI values (0.53-0.78) for pooled data. It is probable that certain characteristics of fall growth such as increased tiller density and reduced rates of leaf elongation (Zarrough et al., 1983; Nelson et al., 1977) caused increases in ground cover with little change in biomass above

the harvested level (5 cm). Because NDVI is heavily influenced by increasing ground cover (Weiser et al., 1986, and Serrano et al., 2000), the small amount of vertical growth observed would have a minimal effect on reflectance values when compared to tillering. This explains why little change in DM was observed with relatively large changes in NDVI values, and why correlations became weaker throughout the growth cycle.

Experiment 2

Rising Plate Calibration

Regression between CSSH and NDVI was inferior in Experiment 2 compared to Experiment 1. Poorer correlations may have been the result of mechanical seed head removal by mowing and by spatial patterns of grazing within each field. This was especially true in areas of dense forage that had been mowed after reproductive growth had begun. While the density of the forage measured may have varied spatially, the sensitivity of the RPM was reduced by stiff pseudo stems (Arias et al., 1990) which prevented the plate from properly compressing the sward. This artifact introduced much error into the calibration of the RPM which was further amplified when the RPM was used to calibrate NDVI. Regardless, both models remained significant (P = 0.0001)

Spatial Dependency of NDVI Data Points

Although with the 0.76 m sampling distance a spatial variability structure could be identified in fields, identifying a lag distance to minimize the number of samples taken or to determine a maximum resolution for data collection could not be accomplished with exponential variogram models. Normally the "range" of a variogram would be reported as the maximum distance of spatial dependency, yet such is not the case with exponential models where the semivariance never reaches a plateau or defines upper limit (Nielsen and Wendroth, 2003). For the exponential model the "range" is simply a model parameter which when multiplied by 3 gives the lag distance at which the sill is within 5% of the asymptote (GS^+, 2005). Therefore, the range parameter for exponential models is not an indicator of the distance at which points remain correlated. However, this does not discount the information obtained from exponential variograms. These models may

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still be used to evaluate greater sampling distances, yet one must keep in mind that greater sampling distances come at the cost of less spatial information.

Effect of Patch Grazing on Dry Matter Distribution

Patch grazing occurred on all fields and influenced the spatial distribution of biomass. Selection of potential grazing areas was the result of several characteristics that are normally associated with cattle grazing behavior. First, in accordance with foraging theory discussed by Stephens and Krebs (1986), cattle inherently search out and consume areas of forage that either do not restrict intake (bite mass) and minimize grazing time or areas that tend to be inhabited with more palatable herbage. Since fields used in Experiment 2 were monocultures of tall fescue, the majority of existing grazed patches may have been the result of animals selecting areas of abundant forage. Second, cattle avoid grazing areas contaminated by fecal material (Aiken et al., 1997). While in some cases of poor nutrition animals may be forced to consume forage in these areas (Cid and Brizuela, 1998), such was not the case with this experiment where animals were removed when forage became inaccessible. Third, the relative proportion of grazed patches to ungrazed patches tends to increase with grazing pressure (Aiken, 1997; Cid and Brizuela, 1998) due to the less selective nature of animals in competitive grazing situations. This would explain why grazed patches in Field 3 (heavy SR) were proportionally larger than Fields 1 (light SR) and 2 (intermediate SR). Fourth, grazing may be inhibited by pseudostems (Arias et al., 1990). When cattle come into contact with pseudostems, their muzzles are unable to penetrate the sward surface without much discomfort to the animal. Therefore, certain high yielding areas in Experiment 2 may be the result of physical barriers created by pseudostems left over from mowing or previous grazing.

Effect of Patch Grazing on Spatial Variability and Regression

Comparison of field variograms (NDVI) reveals that small scale variability was the most pronounced at the intermediate SR. This was a key observation in explaining why a relatively weak correlation was observed between NDVI and CSSH ($R^2 = 0.04$) for Field 2 (intermediate SR), in which the variogram indicated the sharpest increase in the semivariance and the yield map exhibited the most patch grazing. Although patch

grazing had occurred at some level in Fields 1 (light SR) and 3 (heavy SR), their stocking rates reduced the amount of small scale variability. For example the light SR was not high enough to cause extensive patch grazing, leaving large uniform areas of ungrazed forage interspersed with small areas of patch grazing, while the heavy SR was high enough to cause large coalesced grazed patches interspersed with small patches of ungrazed field. These relatively large areas of uniform biomass desensitized the error associated with GPS inaccuracies (Trimble Navigation Limited, 1999) and varying buffer sizes and improved regression models. The patchiness of Field 2 (intermediate SR) exacerbated these sources of error making the regression weaker. Visual representations of these grazed areas can be seen in Figure 14.

Cokriging of Data

When determining whether to use regression or cokriging to determine the best model to estimate biomass, model precision and applicability had to be considered. Regression models estimated yields from a deterministic equation with a standard confidence interval in contrast to cokriging which accounts for spatial uncertainty that changes with distances from validation points. This is because cokriging not only utilizes the correlation between variables but also considers local variability and the fact that validation points have been previously determined. Cokriging provides estimates close to validation points with smaller uncertainty than values calculated farther away, making cokriged estimates more precise. Therefore, when one considers the insignificant difference observed between the mean absolute errors of the CSSH estimates from cokriged buffer data ($error_{abs} = 2.23$) to that of the linear regression model ($error_{abs} = 2.28$), the clear choice becomes the cokriging model.

A successful cokriging operation could not be applied to the raw CSSH and NDVI data sets, due to the failure to achieve positive definiteness (Nielsen and Wendroth, 2003). To achieve positive definiteness, it is required that the two semivariograms and crossvariogram fitted with variogram models must all have the same variogram model type and range. While a common model type (exponential) could be achieved with CSSH and NDVI variograms, a common range could not unless much of the spatial information in one of the variograms was ignored. Cokriging is also

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impractical for producers due to the time, effort, and degree of skill needed to produce and interpret the appropriate spatial statistics needed to analyze spatial data. Therefore, it was concluded that the linear regression would be the better model for estimating biomass

Assumptions for Histogram Analysis

Biomass estimates discussed for fields are based on a hypothetical scenario in which the day of sampling represents the last day of grazing and does not consider grazing beyond the 56 day mark, mainly because daily field growth and animal intake were not estimated. Therefore, values of estimated forage availability were calculated to determine if fields had been over or underutilized and were not used to predict future characteristics of the sward or for predicting future grazing behavior.

Histogram Interpretation

Estimates of herbage biomass above MLNI derived from histograms indicate that all fields had some available forage DM at the time measurements were taken. While total DM above MLNI was minimal for the heavy SR (617 kg DM), it was quite substantial for the light and intermediate SR (3,087 and 2,216 kg DM, respectively). Examination of the skewness and kurtosis of histograms further support DM observations. Kurtosis values for Fields 1 (light SR: 4.75), and 2 (intermediate SR: 3.5) show a relatively high concentration of estimates of biomass over a small range of classes around each mean (2,693 and 2,370 kg DM ha^{-1}, respectively) indicating that the stocking rate had been too low to utilize all the forage in the time frame specified. These observations along with the negative skewness observed for both fields also indicate that animals were patch grazing, with Field 2 (intermediate SR) showing the highest frequency of low yielding areas as indicated by the thicker tail to the left of the distribution curve (Figure. 12) and the more pronounced small scale variability that was observed when field variograms were compared (Figure. 8). In Field 3 (heavy SR) another situation was observed with kurtosis below normal (2.75), a slightly positive skewness (0.27) and a lower mean yield (1,575 kg DM ha^{-1}). These values indicate that animals utilized more of the available forage and were being less selective than cattle on

Fields 1 and 2. Although an excess of available forage was observed for all three fields, only Fields 1 and 2 were consider to be understocked. The mass of available herbage in Field 3 was believed to be the result of vigorous growth around dung patches, and therefore was probably avoided.

Figures

Field 1
(Light SR)

Field 2
(Intermediate SR)

Field 3
(Heavy SR)

NDVI

4,200 kg DM
ha^{-1}

Intensity
Of
Grazing

0 kg DM ha^{-1}
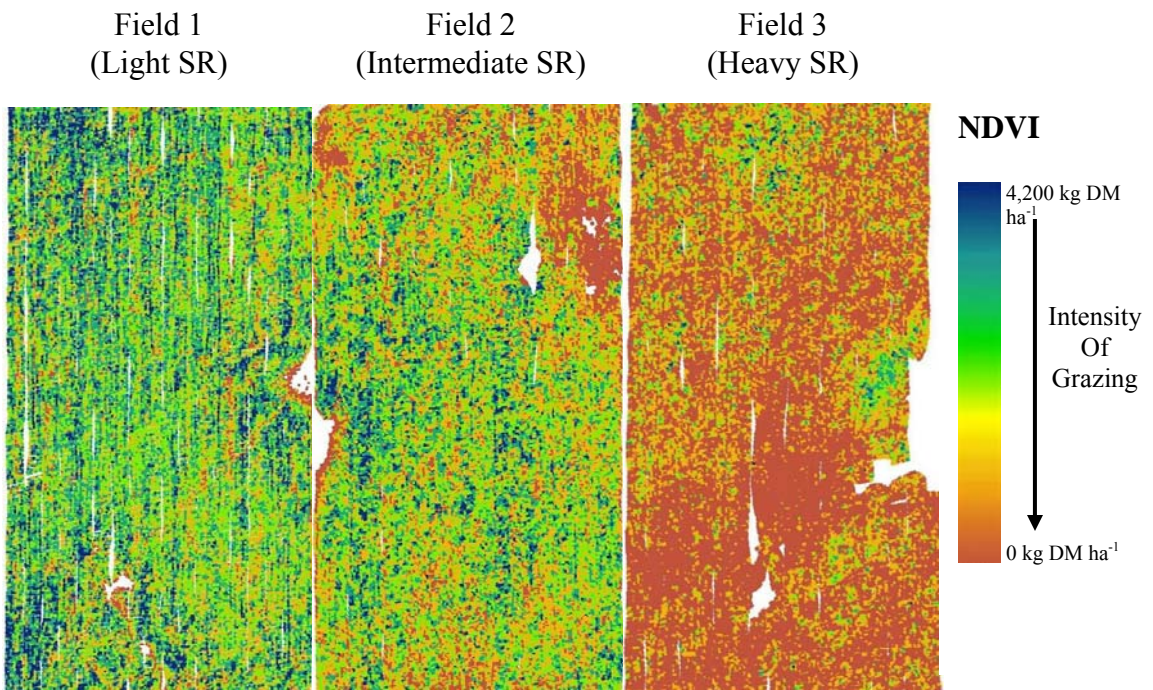
Figure 14. DM yield maps of grazed fields. Maps exhibit the intensity of grazing within each field.

Chapter 6

      It was determined that estimation of biomass from NDVI was best achieved when biomass was estimated by a calibrated rising plate meter. The RPM allowed for more spatially intensive sampling than could be achieved with the direct harvesting method. Also, the non-destructive nature of the RPM allowed repeated measures of biomass over time and minimized interference of future NDVI and RPM measurements.

       Collecting NDVI data at 0.76m spacing was adequate for gathering information about the spatial variability structure of DM within grazed swards. This is especially true when variogram models are needed to evaluate the extent of patch grazing within swards.

      Histograms of sward DM derived from NDVI data sets provided valuable information on grazed swards. Grazed swards may be thoroughly characterized if statistical parameters, such as skewness, kurtosis, mean yield, and mean yield above MLNI, are considered. NDVI collected at a 0.58m resolution provides adequate data for the evaluation of grazing systems and may be used to help with grazing management decisions. We also believe that NDVI at this resolution may be used to evaluate stand densities, identify areas of poor soil fertility, identify the distribution of dung within fields, and provide a easier way to study grazing preference in animals. However, more research is needed to examine the effects of multiple sward species and longer grazing periods on NDVI and yield estimates derived from NDVI.

Appendix
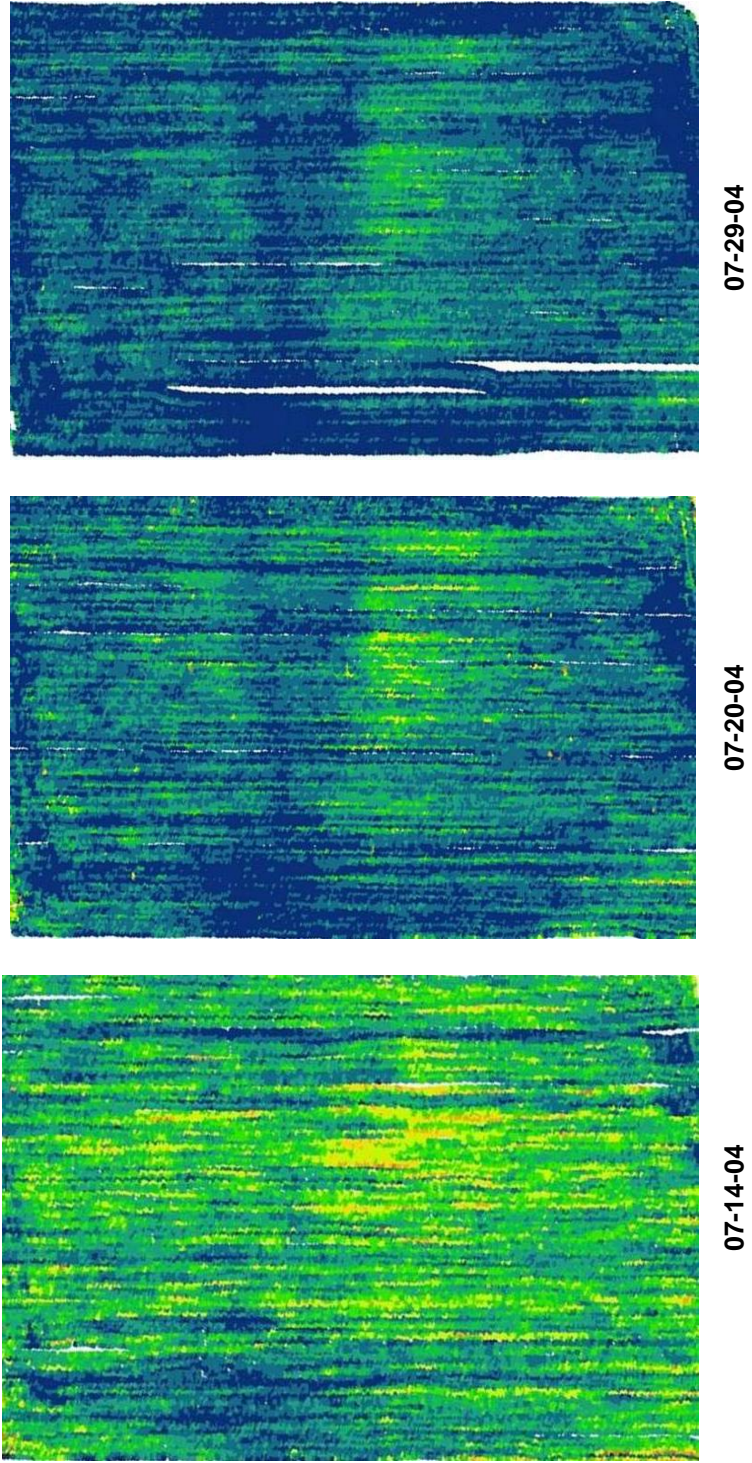
Appendix Figure 1. Change in NDVI From 07-14-04 to 07-29-04

Appendix Figure 3. Buffer layout of Experiment 2. Example of how buffers (2.0m) were laid out within each field using the Buffering Wizard tool in ArcMap 9.0.. Buffers represent areas were CSSH measurements and NDVI values were collected.


Appendix Figure 2. Buffer layout of Experiment 1. Points in the center of the 22.86m buffers represent grid intersections. RPM samples and NDVI values were collected within each buffer to produce regression models.
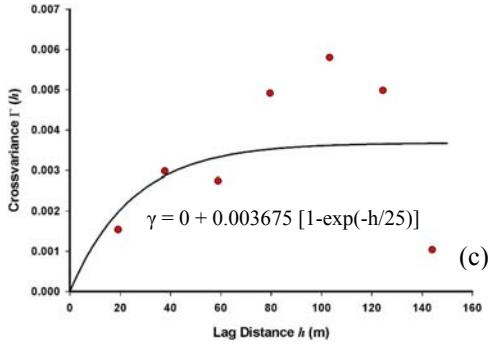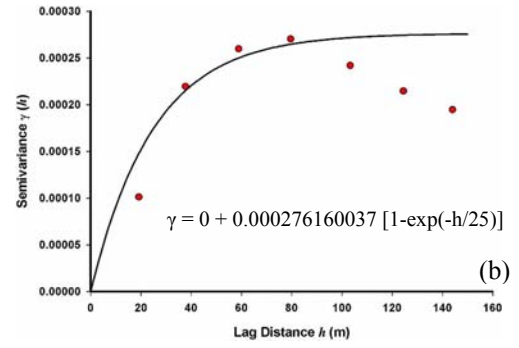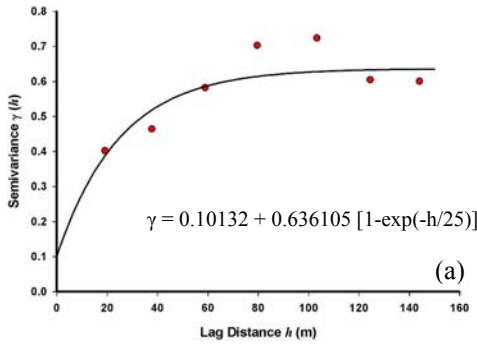
Appendix Figure 4. Variograms of 07-14-04 data from Experiment 1: (a) semivariance of RPM (cm^2) data; (b) semivariance of NDVI data; and (c) crossvariance of RPM and NDVI data.
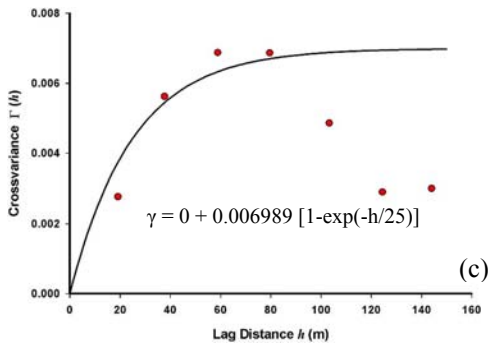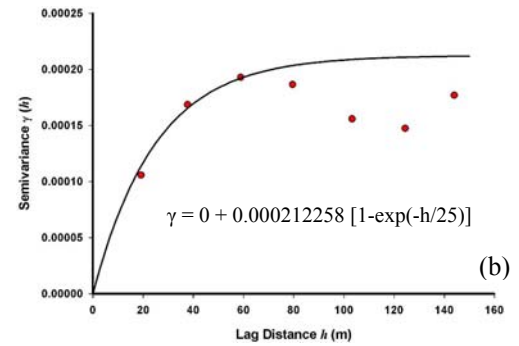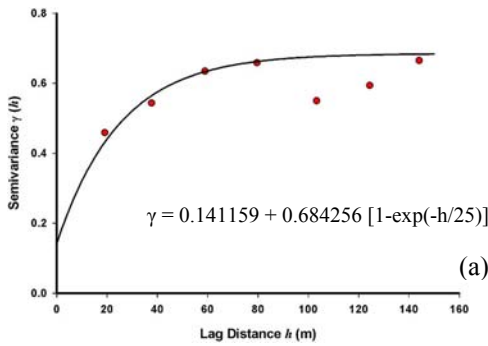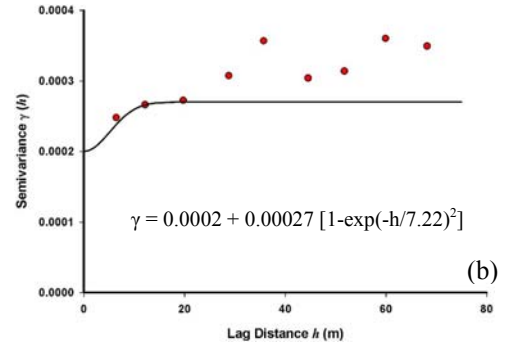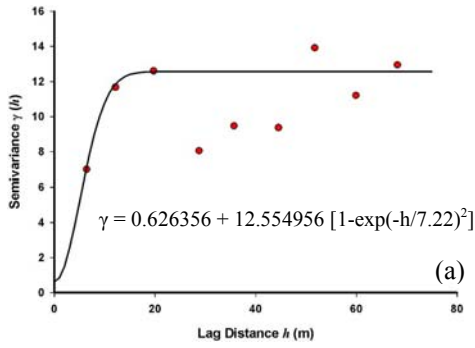

Appendix Figure 5. Variograms of 07-21-04 data from Experiment 1: (a) semivariogram of RPM (cm^2) data; (b) semivariogram of NDVI data; and (c) crossvariogram of RPM and NDVI data.
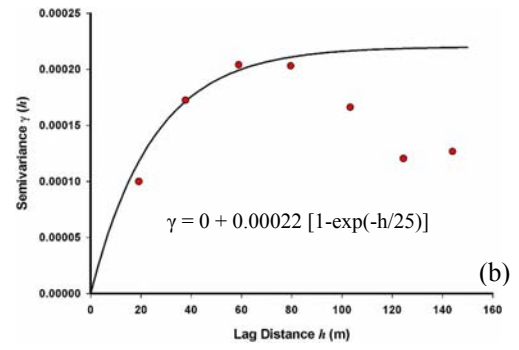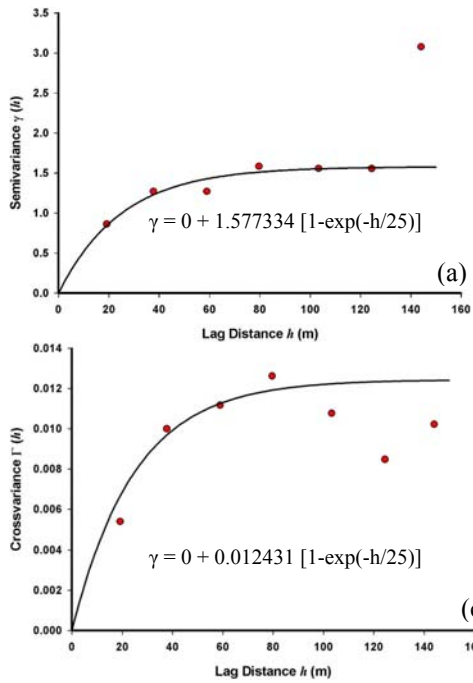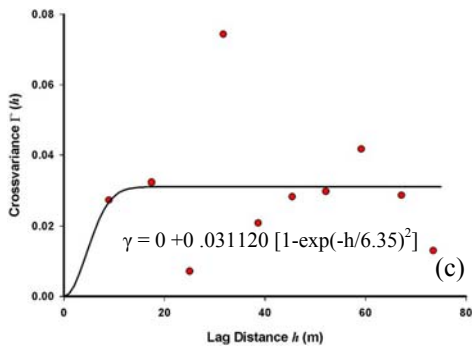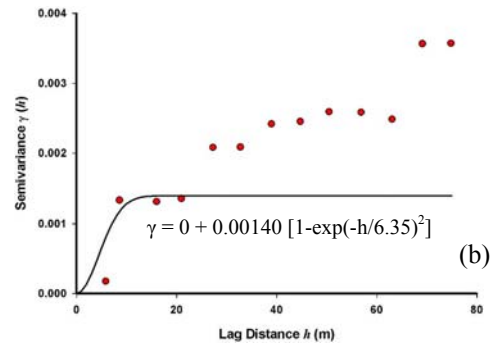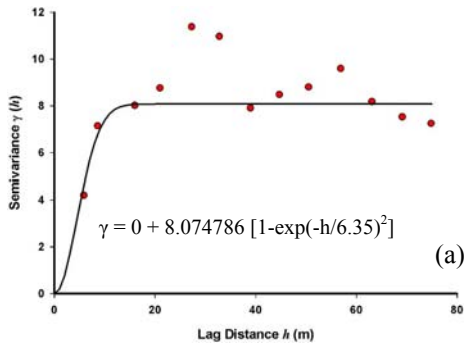
Appendix Figure 6. Variograms of 07-29-04 data from Experiment 1: (a) semivariogram of RPM (cm^2) data; (b) semivariogram of NDVI data; and (c) crossvariogram of RPM and NDVI data.
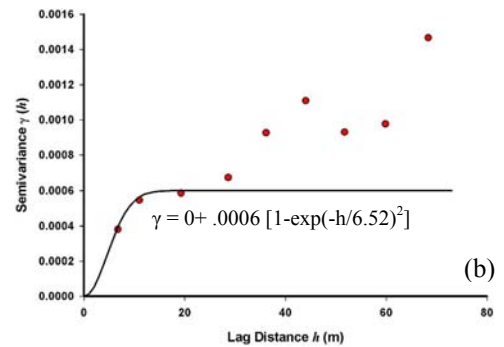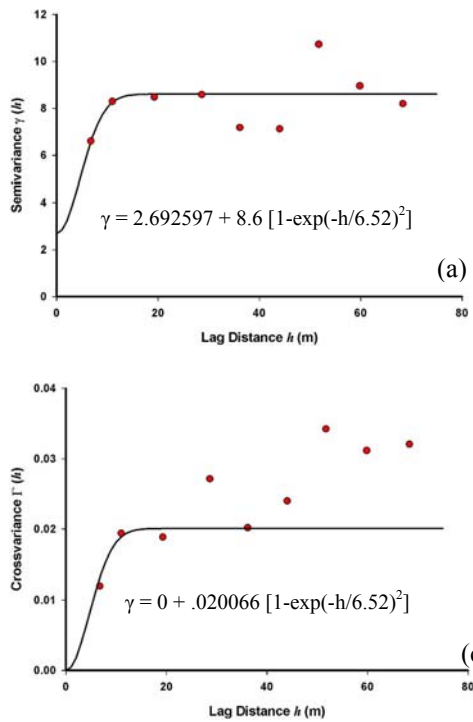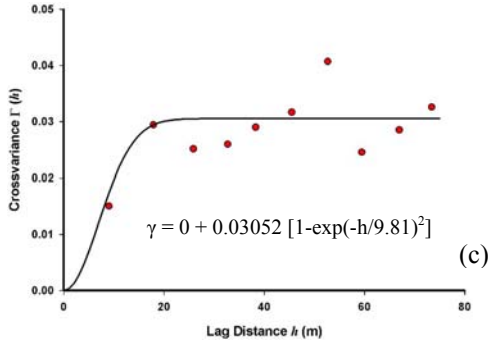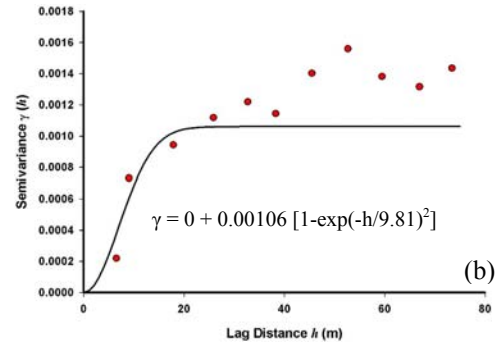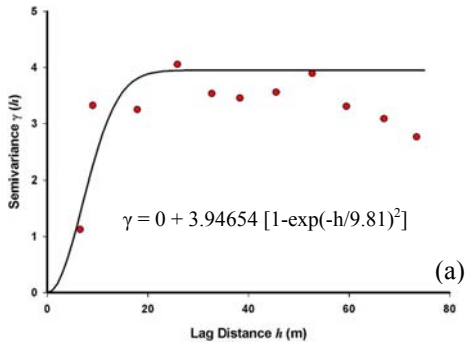

Appendix Figure 7. Variograms of pooled buffer data from Experiment 2: (a) semivariogram of RPM (cm^2) data; (b) semivariogram of NDVI data; and (c) crossvariogram of RPM and NDVI data.

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$\gamma = 0.626356 + 12.554956 \, [1\text{-}\exp(\text{-}h/7.22)^2]$

(a)

$\gamma = 0.0002 + 0.00027 \, [1\text{-}\exp(\text{-}h/7.22)^2]$

(b)

$\gamma = 0.002834 + 0.022741 \, [1\text{-}\exp(\text{-}h/7.22)^2]$

(c)
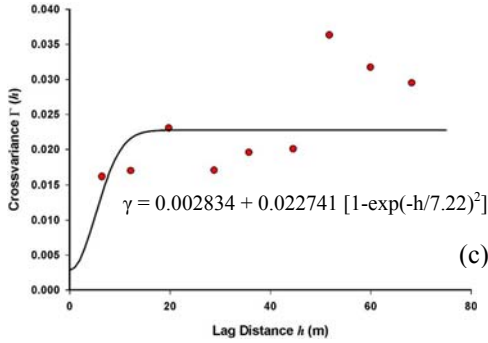
Appendix Figure 8. Variograms of the optimum buffer size (3.0m) for pasture 1 in Experiment 2: (a) semivariogram of RPM (cm^2) data; (b) semivariogram of NDVI data; and (c) crossvariogram of RPM and NDVI data.

$\gamma = 0 + 8.074786 \, [1\text{-}\exp(\text{-}h/6.35)^2]$

(a)

$\gamma = 0 + 0.00140 \, [1\text{-}\exp(\text{-}h/6.35)^2]$

(b)

$\gamma = 0 + 0.031120 \, [1\text{-}\exp(\text{-}h/6.35)^2]$

(c)

Appendix Figure 9. Variograms of the optimum buffer size (0.5m) for pasture 2 in Experiment 2: (a) semivariogram of RPM (cm^2) data; (b) semivariogram of NDVI data; and (c) crossvariogram of RPM and NDVI data.
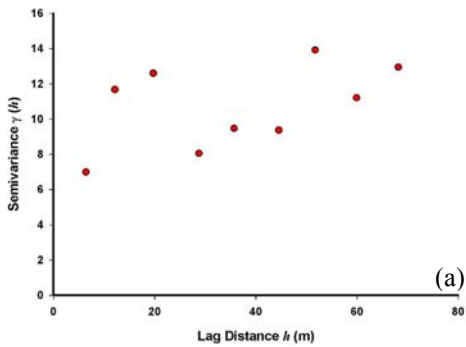
Appendix Figure 10. Variograms of the optimum buffer size (2.0m) for pasture 3 in Experiment 2: (a) semivariogram of RPM (cm^2) data; (b) semivariogram of NDVI data; and (c) crossvariogram of RPM and NDVI data.
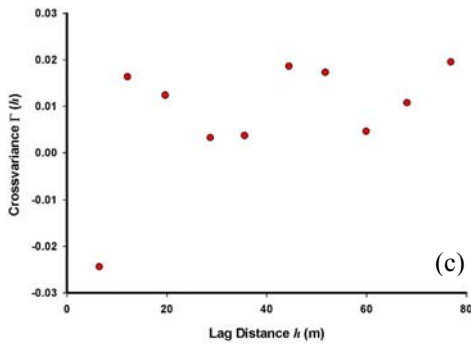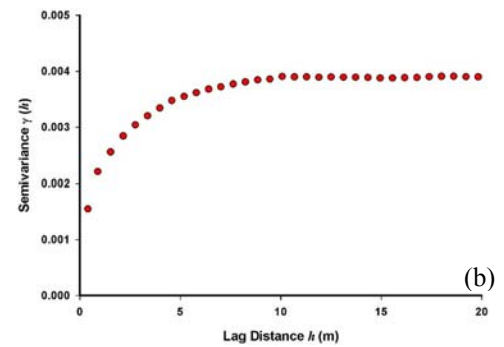
Appendix Figure 11. Variograms of the entire NDVI data set and of the RPM measurements in Pasture 1 of Experiment 2: (a) semivariogram of RPM (cm^2) data; (b) semivariogram of NDVI data; and (c) crossvariogram of RPM and NDVI data. Variograms show the lack of a common range or model type by which variogram could be fit when cokriging was attempted for the prediction of RPM

Appendix Figure 12. Variograms of the entire NDVI data set and of the RPM measurements in Pasture 2 of Experiment 2: (a) semivariogram of RPM (cm^2) data; (b) semivariogra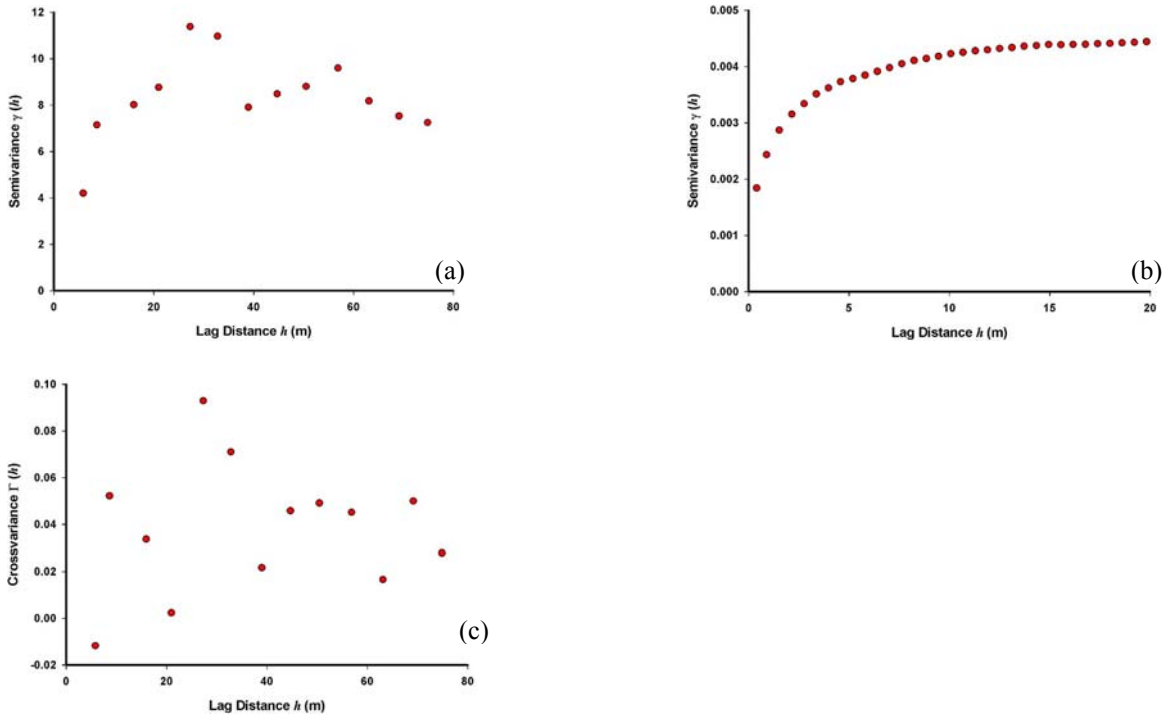m of NDVI data; and (c) crossvariogram of RPM and NDVI data. Variograms show the lack of a common range or model type by which variogram could be fit when cokriging was attempted for the prediction of RPM
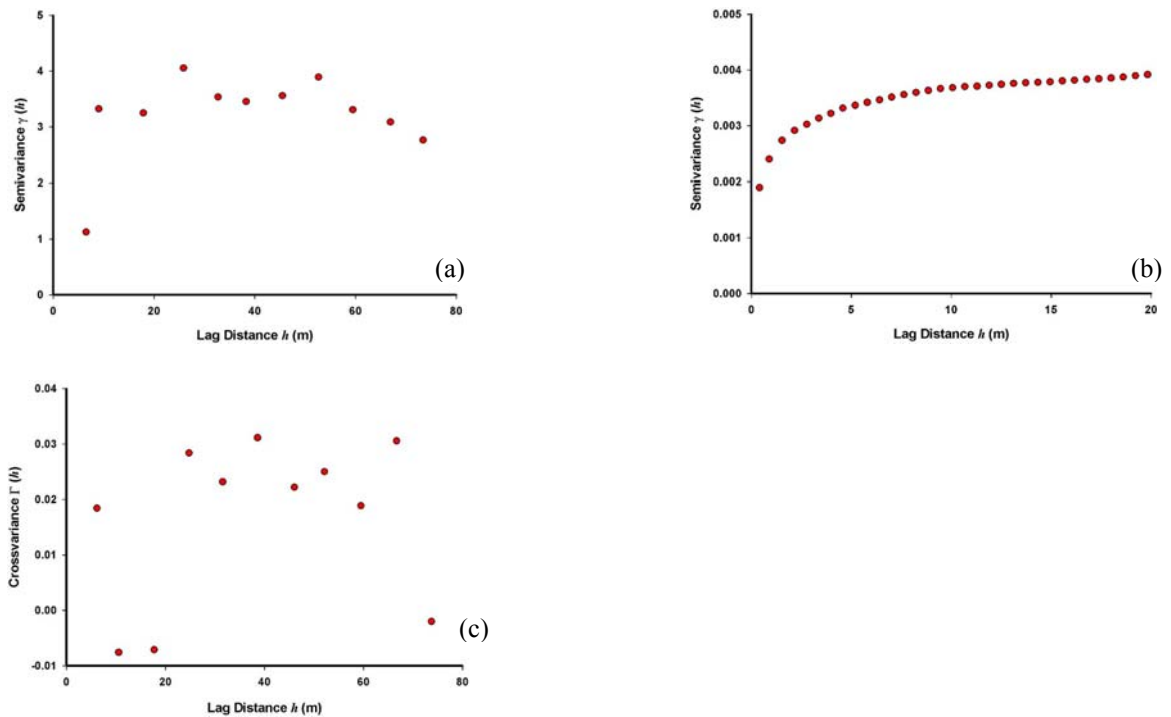

Appendix Figure 13. Variograms of the entire NDVI data set and of the RPM measurements in Pasture 3 of Experiment 2: (a) semivariogram of RPM (cm^2) data; (b) semivariogram of NDVI data; and (c) crossvariogram of RPM and NDVI data. Variograms show the lack of a common range or model type by which variogram could be fit when cokriging was attempted for the prediction of RPM

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