Remote Sensing of Vegetation Water Content from Equivalent Water Thickness using Satellite Imagery

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Abstract

Vegetation water content (VWC) is one of the most important parameters for the successful retrieval of soil moisture content from microwave data. Normalized Difference Infrared Index (NDII) is a widely-used index to remotely sense Equivalent Water Thickness (EWT) of leaves and canopies; however, the amount of water in the foliage is a small part of total VWC. Sites of corn (*Zea mays*), soybean (*Glycine max*), and deciduous hardwood woodlands were sampled to estimate EWT and VWC during the Soil Moisture Experiment 2005 (SMEX05) near Ames, Iowa, USA. Using a time series of Landsat 5 Thematic Mapper, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Advanced Wide Field Sensor (AWiFS) imagery, NDII was related to EWT with R^2 of 0.85; there were no significant differences among land-cover types. Furthermore, EWT was linearly related to VWC with R^2 of 0.87 for corn and 0.48 for soybeans, with a significantly larger slope for corn. The 2005 land-cover classification product from the USDA National Agricultural Statistics Service had an overall accuracy of 92% and was used to spatially distribute VWC over the landscape. SMEX05 VWC versus NDII regressions were compared with the regressions from the Soil Moisture Experiment 2002 (SMEX02), which was conducted in the same study area. No significant difference was found between years for corn (P = 0.13), whereas there was a significant difference for soybean (P = 0.04). Allometric relationships relate the size of one part of a plant to the sizes of other parts, and may be the result from the requirements of structural support or material transport. Relationships between NDII and VWC are indirect, NDII is related to canopy EWT, which in turn is allometrically related to VWC.

Keywords: Corn, *Zea mays*, soybean, *Glycine max*, deciduous hardwood woodland, Soil Moisture Experiment 2005, Normalized difference infrared index, NDII, EWT, VWC, plant allometry

1. Introduction

Accurate estimation of soil moisture content is one of the key steps in monitoring land-atmosphere interactions, global water circulation and carbon cycling (Betts et al., 1996; Koster et al., 2004; Orchard and Cook, 1983). Soil moisture content has been successfully retrieved the last two decades with passive and active microwave techniques at various wavebands (Jackson et al., 1982, O'Neill et al., 1996). However, there is a need for improved algorithms. The Soil Moisture Experiment 2005 (SMEX05) was conducted near Ames, Iowa to validate soil moisture satellite systems and support soil moisture algorithm development (Jackson, 2005). The main goals of this experiment were the validation of soil moisture content, mapping of soil moisture variability, and the study of relationships among soil moisture, vegetation and the atmosphere (Jackson, 2005).

Vegetation water content (VWC, kg m^{-2}), the total amount of water in stems and leaves, is one of the most important parameters for the successful retrieval of soil moisture content from active and passive microwave remote sensing (Jackson et al., 1982, 2004). Sensitivity of soil moisture to VWC in the tau-omega model (Mo et al., 1982) is indicated by the fact that VWC appears in two of the three terms for brightness temperature at the top of a medium with soil and vegetation (Njoku et al., 2003). For example, Bindlish and Barros (2002) states an error of 1 kg m^{-2} in VWC estimation can result in error of 0.1 m^3 m^{-3} gravimetric moisture content for relatively dry soils. If VWC can be estimated using other sensors, then remotely-sensed estimates of soil moisture content with microwave data will be more accurate (Jackson et al., 2004; Anderson et al., 2004; Chen et al., 2005; Yilmaz et al., in press).

The foliar water volume per leaf area (m^3 m^{-2}, conveniently scaled as mm) is termed the equivalent water thickness (EWT) and can be applied to leaves or canopies. Many studies have related foliar water content with reflectances at near-infrared (NIR) and shortwave infrared (SWIR) portion of the spectrum (Tucker, 1980; Hardisky et al., 1983; Hunt & Rock, 1989; Hunt, 1991; Gao, 1996; Cecatto et al., 2002; Fensholt & Sandholt, 2003; Sims & Gamon, 2003; Zarco-Tejada et al., 2003; Maki et al., 2004; Cheng et al., 2006; Davidson et al., 2006; Trombetti et al., in press; Yilmaz et al., in press). The goal is to estimate EWT from satellites like the Moderate Resolution Imaging Spectroradiometer (MODIS) for estimating soil moisture content (Trombetti et al., in press; Yilmaz et al., in print). The problem arises in relating EWT to VWC, since EWT is only a fraction of the total water content per plant.

Allometric relationships ($y = \beta x^{\alpha}$, where the exponent, α, may be 1.0 for a linear equation) are used to characterize the relative growth in leaf and stem biomass (Niklas, 1994; Reddy et al., 1998; Enquist and Niklas, 2002; Jenkins et al., 2004). It is assumed that an allometric relationship exits between VWC and EWT, considering leaves must be supported by stems and stems supply water required for transpiration to the leaves. So the objective of this study is to test the relationship between VWC and EWT for three different vegetation types: corn (*Zea mays*), soybean (*Glycine max*), and deciduous hardwood woodlands. This objective was divided into three steps. First, EWT was estimated using the vegetation data collected during SMEX05 and related to a remote-sensing index. Then, the relationship between EWT and VWC was tested for the three different land cover types. Finally, VWC was related to remotely sensed data from SMEX05 and compared with Soil Moisture Experiment 2002 (SMEX02) vegetation data sets (Anderson et al., 2004; Jackson et al., 2004).

2. Background

Canopy water content has been estimated by various vegetation indices. It is well known that shortwave infrared reflectances (SWIR) are negatively related to the leaf water content due to the large absorption by leaf water (Tucker, 1980; Hunt & Rock, 1989; Ceccato et al., 2001). However, an SWIR band alone is not adequate and it must be contrasted with a NIR band to estimate the VWC, since the other leaf parameters (e.g. internal leaf structure) also affect the SWIR reflectance (Hunt & Rock, 1989; Gao, 1996; Ceccato et al., 2001).

For this study, a combination of SWIR and NIR bands was used to calculate Normalized Difference Infrared Index (NDII) from Hardisky et al. (1983):

$$NDII = (\rho_{0.85} - \rho_{1.65}) / (\rho_{0.85} + \rho_{1.65}) \qquad (1)$$

where $\rho_{1.65}$ and $\rho_{0.85}$ are the reflectances at 1.65µm and 0.85µm wavelengths, respectively.

Based on the analysis of reflectance spectra and careful consideration of the scattering and absorption properties of the atmosphere and vegetation canopies, Gao (1996) developed the Normalized Difference Water Index (NDWI):

$$NDWI = (\rho_{0.85} - \rho_{1.24}) / (\rho_{0.85} + \rho_{1.24}) \qquad (2)$$

where $\rho_{1.24}$ is the reflectance at 1.24µm wavelength. NDWI saturates at higher LAI values compared to NDII, due to its weaker liquid water absorption feature. The reason NDII was used in this study is that medium-spatial-resolution multispectral sensors [Landsat 5 Thematic Mapper

(TM), Advanced Wide Field Sensor (AWiFS), and Advanced Spaceborne Thermal Emission and Reflection Radiometer(ASTER)] have bands at 1.65 µm wavelength, but not at 1.24 µm wavelength.

NDII has been studied by numerous authors under different names. Kimes et al. (1981) called this index ND45 because it was a normalized difference of Landsat TM bands 4 and 5. They used this index to examine biophysical variables of crops; NDII performed about the same as the normalized difference vegetation index (NDVI). Hardisky et al. (1983) showed NDII was related to canopy water content, and provided a name (used here) that does not to refer specifically to a single sensor. Fensholt and Sandholt (2003) coined the name shortwave infrared water stress index, SIWSI(6,2), because they used MODIS band 2 and 6 reflectances to observe water stress in a semiarid environment. Jackson et al. (2004), Maki et al. (2004), and Verbesselt et al. (2007) used NDII to estimate VWC or EWT, but referred to the index as NDWI. Xiao et al. (2005) referred to NDII as the Land Surface Water Index (LSWI) using MODIS bands 2 and 6 for paddy rice landcover mapping.

3. Methodology

3.1. Site description

The Walnut Creek watershed, south of Ames, Iowa, USA, has been the focus of research by USDA-ARS National Soil Tilth Laboratory (Hatfield et al., 1999). This region was used for the Soil Moisture Experiment 2002 (SMEX02; Anderson et al., 2004; Jackson et al., 2004) and the Soil Moisture Atmospheric Coupling Experiment (SMACEX; Kustas et al., 2004).

For SMEX05, a regional study area and a smaller intensive study area were selected (Jackson, 2005). The intensive study area is located between 41° 52´ N and 42° 04´ N latitude, and 93° 31´ W and 94° 01´ W longitude, for a total area of 22 km by 41 km (Jackson, 2005). The study areas in SMEX05 were extended west compared to SMEX02 in order to cover deciduous hardwood woodlands along the Des Moines River (Fig. 1A). The dominant land cover in central Iowa is cropland, where corn and soybean cover nearly 90% of the Walnut Creek watershed (Doraiswamy et al., 2004). Topography ranges between 280 m to 330 m with an average elevation of 310 m. The climate is humid with mean average temperature of 10.7 °C. Average annual rainfall is 835 mm and the heaviest precipitation months are May and June with about one third of the annual total (Jackson, 2005).

Daily sampling for soil moisture content over the intensive study area was a major objective of SMEX05 (Jackson, 2005). The same crop fields and woodland sites were used for both soil moisture and vegetation sampling. Fields with the dominant land cover, corn and soybean, were sampled weekly during the experiment from 15 June to 05 July 2005 to obtain a large range in EWT and VWC. Five deciduous hardwood woodland sites were sampled once, because large changes in EWT and VWC were not expected.

3.2. Crop EWT and VWC

At each field, 5 plots were established 50 m apart with directions alternating 90° across and along the rows from the field's entry point. Plots were geolocated with a Garmin (Olathe, Kansas, U.S.A.) eTrex Legend global positioning system enabled with the wide-area augmentation system (4-8 m accuracy).

For each field, row direction and spacing were determined; almost all rows were 30 inches apart (0.76 m). For each plot, plant density was estimated by counting the number of plants in two adjacent rows over a transect length of 10.00 meters. Average plant height and canopy cover were estimated using a meter stick. The number of leaves on an average-looking plant per plot was counted to estimate vegetative growth stage.

One average-looking plant per plot was cut at ground level, placed in a paper bag, sealed in a plastic bag, and placed in a cool dark container to avoid water loss as much as possible. Upon return, leaves and stems were separated and weighed. Plant leaf area was measured using a LI-3100c leaf area meter (Li-Cor, Inc., Lincoln, Nebraska, USA). Stems and leaves were dried for 48-72 hours at 60 °C and weighed.

Leaf equivalent water thickness (EWT_{leaf}, mm) was calculated:

$$EWT_{leaf} = (FWT_{leaf} - DWT_{leaf}) / dw\, A_{leaf} \quad (3)$$

where A_{leaf} is the leaf area (m^2), FWT_{leaf} is the leaf fresh weight (kg), DWT_{leaf} is the leaf dry weight (kg), and dw is the density of liquid water (1000 kg m^{-3}). VWC (kg m^{-2}) was calculated:

$$VWC = \eta \cdot [(FWT_{leaf} - DWT_{leaf}) + (FWT_{stem} - DWT_{stem})] \quad (4)$$

where η is plant density (number m^{-2}), and FWT_{stem} and DWT_{stem} are the stem fresh and dry weights (kg), respectively.

Leaf area index (LAI, m^2 leaf m^{-2} ground area) was measured for each crop plot using an LI-COR, Inc. (Lincoln, Nebraska, USA) LAI-2000 Plant Canopy Analyzer. The LAI-2000 measurements were taken along the 10-m transect. This technique was applied under diffuse skylight conditions whenever possible (Wells & Norman, 1991). For some sites on some dates, LAI was measured by under direct sunlight; hence, LAI was increased 10% for these plots (John Norman, personal communication 2004; Anderson et al., 2004; Yilmaz et al., in press). Canopy EWT (EWT_{can}, mm) was calculated:

$$EWT_{can} = LAI \cdot EWT_{leaf} \tag{5}$$

where LAI is the corrected leaf area index. Values of LAI were checked for outliers by multiplying the leaf area of an average plant times the plant density (η).

3.3. Woodland EWT and VWC

Deciduous hardwood woodlands occur in the study area near creeks, streams and the Des Moines River, where the topography is generally too steep to cultivate. At each of 5 sites, 4 plots were established along the path for monitoring soil moisture. Generally, each plot was 25 m by 25 m, although depending on the local topography, the sizes of some plots were smaller. For each tree over 2 m height, species was determined and diameter (cm) at 1.3 m height was measured. Average height of the trees in the plot was estimated using an inclinometer at 50-m distance.

At each plot, leaf samples were collected with a pruning pole having a maximum reach of 4.5 m. The leaves were placed in paper bags, and stored as above. Upon return, leaves were weighed and the areas measured using the LI-3100c leaf area meter. The samples were then dried 48 hours at 60 °C and weighed.

With the average height of the plots ranging from 20 m to 30 m, it was not possible to sample leaves from the top of the canopy; hence, all of the leaf samples collected were considered shade leaves (Abrams & Kubiske, 1990). For hardwoods and conifers in the central United States, Abrams & Kubiske (1990) found there are large differences in specific leaf area (kg m^{-2}) between sun leaves and shade leaves. It is assumed that specific leaf area is related to leaf thickness (Knapp & Carter, 1998) and thus to leaf water volume. Therefore, the ratio of specific leaf area of sun leaves to shade leaves (Abrams & Kubiske, 1990) was used to estimate EWT_{leaf} from the measured data on shade leaves.

LAI was measured with hemispherical digital photographs (Yilmaz et al., in press) at five locations in each plot. Zhang et al. (2005) showed that the hemispherical photos with automatic exposure settings underestimated LAI; therefore, a calibration equation based on the Li-Cor LAI-2000 was applied (Yilmaz et al., in press). Then, EWT_{leaf} and EWT_{can} of the woods were calculated with Equations 3 and 5, respectively.

For selected trees, wood cores of 3 mm in diameter and about 10 cm in length were taken by drilling at 1.3 m height with an increment borer. The core samples were placed in plastic bags, and stored as above. Core fresh weights (FWT_{core}, kg) and dry weights (DWT_{core}, kg) were recorded upon return and after drying for 48-72 hours at 60 °C, respectively. The density of wood (d) was taken to be 600 kg m^{-3}, an average value for deciduous hardwood species in the region (Birdsey, 1992). Tree wood volume (V, m^3) was calculated using region-specific equations based on stand height and tree diameter (Hahn & Hansen, 1991), in which the stand site index was estimated by the stand height. Woodland VWC (kg m^{-2}) was calculated:

$$VWC = \Sigma V \cdot (1 - DWT_{core} / FWT_{core}) \cdot d / A + LAI \cdot EWT_{leaf} \cdot dw \qquad (6)$$

where ΣV *is* the wood volume (m^3) summed for each tree in the plot, A is the plot area (m^2), *dw* is the density of liquid water, and LAI and EWT_{leaf} are the corrected values.

3.4. Satellite Data

For SMEX05, a time series of 8 scenes from Landsat 5 TM, 4 scenes from AWiFS and 2 scenes from ASTER satellites were acquired, georeferenced and atmospherically corrected (Table 1). The study site was mostly under clouds for the 9 August TM scene and two scenes (22 June TM and 1 July TM) have about 40% cloud cover, so these images were not processed further. The path 27/row 31 TM scenes and both ASTER scenes did not cover the full study area. The scenes were registered by using the Environment for Visualizing Images (ENVI) version 4.1 (Research Systems, Inc., Boulder CO, USA).

Digital numbers for TM, AWiFS and ASTER images were converted into radiances and then atmospherically corrected into land-surface reflectances (Yilmaz et al., in press). The atmospheric correction for all the channels was made using the MODTRAN model (Adler-Golden et. al., 1999). As input data for MODTRAN, sun photometer data were obtained through the NASA Goddard Space Flight Center AERONET network (http://aeronet.gsfc.nasa.gov) for the site in Ames, Iowa (located in the SMEX05 intensive study area). Ozone content data were obtained from Environment Canada (http://woudc.ec.gc.ca/cgi-bin/selectMap/), radiosonde data were obtained from National Oceanic and Atmospheric Administration (http://raob.fsl.noaa.gov/), and meteorological data were obtained from nearby weather stations. NDII (Fig. 1B) was calculated using Equation 1 from the land-surface reflectances (Fig. 1A).

The 2005 USDA National Agriculture and Statistics Service (NASS) 30-m land-cover classification for the state of Iowa was acquired (http://www.usda.gov/nass/). The NASS land-cover classification was compared to ground data acquired during SMEX05. Teams of people drove around the SMEX05 study area, observed the land cover type, and determined latitude and longitude using a Garmin global positioning system. The accuracy of the classification was assessed using the methods of Congalton & Green (1999).

4. Results and Discussion

4.1. Time course of NDII

Starting with the ASTER image on 22 May 2005 (Table 1), NDII for soybean and corn fields were low at about -0.35 to -0.30, the values for bare soil, and increased over time until mid July (Fig. 2). The NDII for corn, soybean, and woodland sites showed large differences in June, averaging -0.1 for soybean, 0.1 for corn, and 0.3 for woodland sites (Fig. 2). In July and August, NDII for corn and soybean was equal to that for woodlands. NDII for the woodland plots showed no trend over time (Fig. 2), because spring leaf-out occurred about four weeks prior to the first image acquired.

There were no apparent differences in NDII calculated from the different multispectral sensors, therefore the data were combined to examine the relationship of NDII to EWT during SMEX05. Whereas the differences in band pass for the different sensors will create differences in NDII for the same pixel on the same date, the differences in NDII were probably small compared to the change in NDII over time for corn and soybean, and may be small compared to possible errors from the atmospheric correction. The effect of sensor on NDII value would have been tested if scenes from the TM, ASTER or AWiFS were acquired for the same date.

4.2. Landcover

Based on the NASS classification, the dominant landcover type for the study area was cropland, with 34% of the area in corn and 30% of the area in soybean (Fig.3). Moreover pasture and woodlands cover 17% and 12% of the study area, respectively. The SMEX02 study area (100 by 50 km; Doraiswamy et al., 2004) was centered 25 km to the east of the SMEX05 study area and did not include the woodlands next to the Des Moines River. The differences in the percent cover of crops (90% for SMEX02 and 65% for SMEX05) are due to offset distance between the study areas.

The NASS classification has an overall accuracy of 92% for the SMEX05 area (Table 2). The k-hat statistic is 0.88 ± 0.021 standard error, so the classification is highly significant ($P < 0.001$). Corn and soybean fields were classified with high user and producer accuracies, whereas most of the alfalfa fields on the ground were classified as soybean (Table 2). Two of the woodland sites were misclassified as other crops (e.g. canola, flaxseed, safflower) and as an urban area. Furthermore some of the corn fields were misclassified as woodland resulting in a user accuracy of 79% for woodlands.

4.3 LAI - EWT – NDII

From the start to the end of SMEX05, LAI for corn increased from 0.37 to 3.29 and LAI for soybean increased from 0.16 to 1.97 m^2 m^{-2}. EWT_{leaf} increased from 0.26 to 0.29 mm for corn and from 0.16 to 0.19 mm for soybean, because the newer larger leaves tended to be thicker. Therefore, EWT_{can} increased from 0.11 to 0.91 mm for corn and from 0.02 to 0.57 mm for soybean (Fig. 4).

Uncorrected mean LAI (± standard deviation) was 2.32 ± 0.39 m^2 m^{-2} for the deciduous hardwood woodland sites. Because the hemispherical photographs were not underexposed (Zhang et al., 2005), the resulting woodland LAI were much lower than expected. Using the calibration from Yilmaz et al. (in press), the corrected mean LAI was 4.24 ± 0.75 m^2 m^{-2}. The shade-leaf EWT averaged 0.08 mm. With the sun-shade leaf correction (Abrams & Kubiske, 1990), the average leaf EWT was 0.16 mm, which is much closer to the values for other deciduous hardwood species (Hunt & Rock, 1989; E. R. Hunt, Jr., unpublished data). Therefore, the average canopy EWT (corrected for both LAI and sun-shade leaf EWT) was 0.62 ± 0.17 mm.

For the same period, NDII values increased from -0.07 to 0.45 and from -0.18 to 0.17 for corn and soybean, respectively, whereas NDII for the woodland sites averaged 0.37. NDII was linearly related to canopy EWT for corn, soybean and woodland (Fig. 4). Using dummy variables to separate the effects of species on the NDII – EWT relationship (Fig. 4), the regression equation for soybean was significantly different from the equations for corn and woodland (P = 0.02). However, analysis of the residuals indicated that 6 soybean plots sampled on the first two days (low LAI from 0.16 to 0.25 m^2 m^{-2}) strongly biased the regression coefficients. Very low LAI was also associated with very low soybean cover, where the reflectance of the soil or multiple scattering between plant and soil could overwhelm the signal from vegetation (Ray and Murray, 1996). When the 6 plots were removed from the analysis, the regression equations for soybean and woodlands were not significantly different from the equation for corn (P = 0.14 and P = 0.07, respectively). The overall NDII – EWT regression equation (Fig. 4) has R^2 of 0.85 and the standard error of y estimate of 0.093 mm, which is about equal to an LAI of 0.5 m^2 m^{-2}. The strong linear relationship between canopy EWT and NDII over the range of data obtained during SMEX05 supports the conclusions of previous studies (Yilmaz et al., in press; Ceccato et al., 2002; Davidson et al., 2006). Data from Hunt (1991) and SAIL model simulations (not shown) indicate that the NDII – EWT relationship will begin to saturate at NDII from 0.4 to 0.5.

4.4. VWC – EWT

VWC was linearly related to canopy EWT for each crop type (Fig. 4). For the corn and soybean regression equations respectively, the R^2 were 0.87 and 0.48 and the standard error of y estimates were 0.49 and 0.17 kg m^{-2} (Fig. 5). The VWC – EWT regressions of corn and soybean were significantly different using dummy variable regression ($P < 0.001$; Fig. 5).

On the other hand, there was no significant relationship between woodland VWC and canopy EWT ($P = 0.81$; Fig. 6). The DWT_{core}/FWT_{core} ratio averaged 0.573 ± 0.0747. There were too few data to detect differences among species. Using a single factor Analysis of Variance (ANOVA), there was no significant difference in DWT_{core}/FWT_{core} among sites ($P =$ 0.25). Thus, the primary variation in VWC of deciduous hardwood woodlands was stand wood volume, determined primarily from tree diameter and density. Canopy EWT was a small fraction of total VWC (Fig. 6), so there was no ability to predict VWC from NDII. Therefore, woodland VWC was assigned the average plot value of 5.01 kg m^{-2} for regional analyses.

Tree wood volume and leaf area have strong allometric relationships with tree diameter (Niklas, 1994; Jenkins et al., 2004), so a relationship between VWC and EWT was expected but not found (Fig. 6). There may be a stronger relationship between tree sapwood cross-sectional area at 1.3 m height and leaf area because of the requirement for the active xylem to supply water to the leaves for transpiration (Waring et al., 1982). For trees, several years of annual xylem growth may supply water to the foliage, whereas for annual crops, increases in xylem and leaf area are highly coordinated (Hunt et al., 1991). Thus, the allometric relationship between EWT and VWC was expected to be stronger for crops compared to woodlands. Besides water flow, stems also provide mechanical support for leaves, which contribute to the allometric relationships between stem and leaves (Niklas, 1994).

One reason for no correlation between VWC and EWT for woodlands (Fig. 6) is that the variation about the allometric regression may be as much as an order of magnitude for trees (Enquist and Niklas, 2004). Variation in tree biomass may range up to three or four orders of magnitude, so there may have been an insufficient range in the data (Fig. 6) to obtain a statistically significant relationship. Most allometric relationships are determined for individual plants, and the coefficients may be dependent on plant density (Enquist and Niklas, 2004). The deciduous hardwood plots had large differences in tree density, whereas soybean and corn are grown under relatively uniform densities.

4.5. VWC –NDII

Based on a strong linear relationship between VWC and EWT, and between EWT and NDII, VWC was linearly related to NDII for corn and soybean (Fig. 7). The standard error of *y* estimates for the SMEX05 regression equations were 0.46 mm and 0.09 mm for corn and soybean, respectively, and the R^2 values for the SMEX05 regression equations were 0.89 and

0.87 for corn and soybean, respectively. Then the regression equations were compared with the equations from SMEX02 (Anderson et al., 2004; Jackson et al., 2004); the regression equations for soybean were significantly different between the two years (*P* = 0.04), whereas the regression equations for corn were not significantly different (*P* = 0.13). Reddy et al. (1998) concluded water stress affects allometric relationships in soybean, so perhaps the differences in soybean regression equations between 2002 and 2005 (Fig. 7) were the result of differences in weather.

4.6. Regional VWC

Using classification of land cover types (Fig. 3), regional VWC was mapped using NDII (Fig. 8). VWC is an important parameter in the tau-omega model for retrieving soil moisture content (Mo et al., 1982; Crosson et al., 2005), and soil moisture content can be determined if the VWC is under 5 kg m^{-2} (Jackson, 1993). However, from the NDII-VWC regression equation for corn (Fig. 7), VWC of 5 kg m^{-2} will occur when NDII is saturated, so VWC = 4 kg m^{-2} was selected as the limit for a regional analysis of VWC (Fig. 8). The fractional area of VWC $\geq$ 4 kg m^{-2} may be a key input into future algorithms for soil moisture content.

For the 23 June AWiFS image (Fig. 8) and earlier, 12% of the region had VWC $\geq$ 4 kg m^{-2}, these areas were the woodlands in which NDII could not be used to determine VWC. However, for the 17 July Landsat 5 TM image, 35% of the region had VWC $\geq$ 4 kg m^{-2}, because of the growth of corn (data not shown). Thus, the fractional area in which microwave data are sensitive to changes in soil moisture may change dramatically over a short period of time, showing methods are required to monitor these changes.

Therefore, over a region, landcover classification can either mask out areas where microwave data are potentially insensitive to soil moisture content, forests and woodlands with high expected VWC, or be used to assign allometric relationships. If sensitivity to VWC is required between 4 and 5 kg m^{-2}, then other sensors such as lidar (Lefsky et al., 2002) may need to be included. However, for many vegetation classes, NDII can be used to estimate changes in VWC over the growing season, assuming a stable allometric relationship exists between VWC and EWT.

5. Conclusions

First, this study is another contribution indicating there is a linear relationship between NDII and EWT, before NDII saturates at high canopy EWT. Canopy EWT was largely determined from LAI but also from changes in leaf EWT as new leaves were added. Trombetti et al. (in press) showed that inversion of MODIS data using canopy reflectance models can be used to get good estimates of EWT. This study and Yilmaz et al. (in press) show that NDII would make a good backup algorithm for production of data products from MODIS.

The relationship between NDII and VWC was shown to be indirect, based on the allometric relationships between canopy EWT and VWC, and the linear relationship between canopy EWT and NDII. However, NDII saturates around 0.4 to 0.5, which interfered with estimation of VWC in corn from 4 to 5 kg m^{-2}, the sensitivity limit for detection of soil moisture content using microwave sensors. However the rapid change of VWC in crops indicates that remotely-sensed indices, such as NDII, are required for integration with microwave data.

Because EWT is a small fraction of VWC for many vegetation types, remotely-sensed EWT will not be used itself for microwave retrievals of soil moisture content. Land-cover classification is used in two ways: first, it will allow selection of the appropriate allometric relationship between EWT and VWC, and second, it will be used to mask out areas with high expected VWC.

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Table 1

Dates of image acquisition during Soil Moisture Experiment 2005 (SMEX05)

Sensor	Path/Row	Dates
TM 5	26/31	30 May, 1 Jul[1], 17 Jul, 18 Aug
TM 5	27/31	6 Jun, 22 Jun[1], 24 Jul, 9 Aug[1]
AWiFS	275/39/Quad c	23 Jun
AWiFS	272/41/Quad a	2 Jul
AWiFS	274/41	12 Jul
AWiFS	274/39/Quad c	29 Aug
ASTER	n/a	22 May
ASTER	n/a	9 Jul

[1] heavy cloud cover

Table 2

Accuracy assessment of the USDA National Agricultural Statistics Service (NASS) land cover classification for the SMEX05 study area.

	Ground Data					
Class	Corn	Soybean	Woodland	Alfalfa	Total	User Accuracy (%)
Corn	210	4	2	-	216	97
Soybean	1	122	-	8	131	93
Woodland	12	-	46	-	58	79
Alfalfa	1	-	3	6	10	60
Other[1]	-	-	2	-	2	0
Total	224	126	53	14	417	-
Producer Accuracy (%)	94	97	87	43	-	-
Overall Accuracy						92 %

[1] Urban area and other crops (canola, flaxseed, safflower)

Fig. 1. A) AWiFS false-color composite for 23 June 2005. The black rectangular box is the Soil Moisture Experiment 2005 (SMEX05) study area of 22 km in the North-South and 41 km in the East-West directions, where North is to the top of the image; B) Normalized Difference Infrared Index (NDII) for 23 June 2005.

Fig. 2. Change of Normalized Difference Infrared Index (NDII) over time for the five woodland sites and representative fields of corn and soybean. Letters for each date indicate the sensor used to acquire the imagery: (A) Advanced Spaceborne Thermal Emission and Reflection Radiometer, ASTER; (T) Landsat 5 Thematic Mapper; and (W) Advanced Wide Field Sensor, AWiFS.

Fig. 3. USDA NASS land classification of the SMEX05 study area. Asterix symbols indicate the location of vegetation sampling sites. The overall accuracy of the classification is 92%.

Fig. 4. Relationship between canopy Equivalent Water Thickness (EWT), and Normalized Difference Infrared Index (NDII) for corn, soybean and deciduous hardwood woodland. The regression line is $y = 1.1767x + 0.2303$ with R^2=0.85 and a standard error of y estimate = 0.091 mm.

Fig. 5. Relationship between total Vegetation Water Content (VWC) and canopy Equivalent Water Thickness (EWT) for corn and soybean. Total VWC is the sum of stem and canopy water content. The equation for corn is $y = 5.3538\ x - 0.31$ and for soybean is $y = 1.3711\ x + 0.041$ with

R^2 for corn = 0.87 and R^2 for soybean = 0.48. The standard error of *y* estimates are 0.49 and 0.17 kg m^{-2} for corn and soybean, respectively.

Fig. 6. Relationship between VWC and canopy EWT for deciduous hardwood woodlands. There was no significant correlation between canopy EWT and VWC (P = 0.81). The mean VWC for all plots was 5.01 kg m^{-2} with a standard deviation of 2.51 kg m^{-2}.

Fig. 7. Comparison of VWC and NDII between SMEX05 and Soil Moisture Experiment 2002 (SMEX02). Equation for the SMEX05 corn regression is $y = 7.694\ x + 0.7523$ (dotted line) with R^2 of 0.89 and standard error of *y* estimate of 0.46 mm. Equation for SMEX05 soybean regression is $y = 2.2237\ x + 0.3778$ (dashed line) with R^2 of 0.87 and standard error of *y* estimate of 0.09 mm. Equation for the SMEX02 corn regression is $y = 9.054\ x + 0.167$ with R^2 of 0.78 and standard error of y estimate of 0.49 mm. Finally, the equation for SMEX02 soybean regression is $y = 1.3464\ x + 0.433$ (solid line) with R^2 of 0.615 and standard error of *y* estimate of 0.19 mm. SMEX05 and SMEX02 corn regressions are not significantly different (P = 0.13); the overall regression is y = 7.806x + 0.6894, whereas soybean regressions are significantly different (P = 0.04).

Fig. 8. VWC (kg m^{-2}) of corn and soybean for 23 June 2005 from AWiFS imagery. Woodlands were assumed to have constant VWC of 5 kg m^{-2}.

Figure 1
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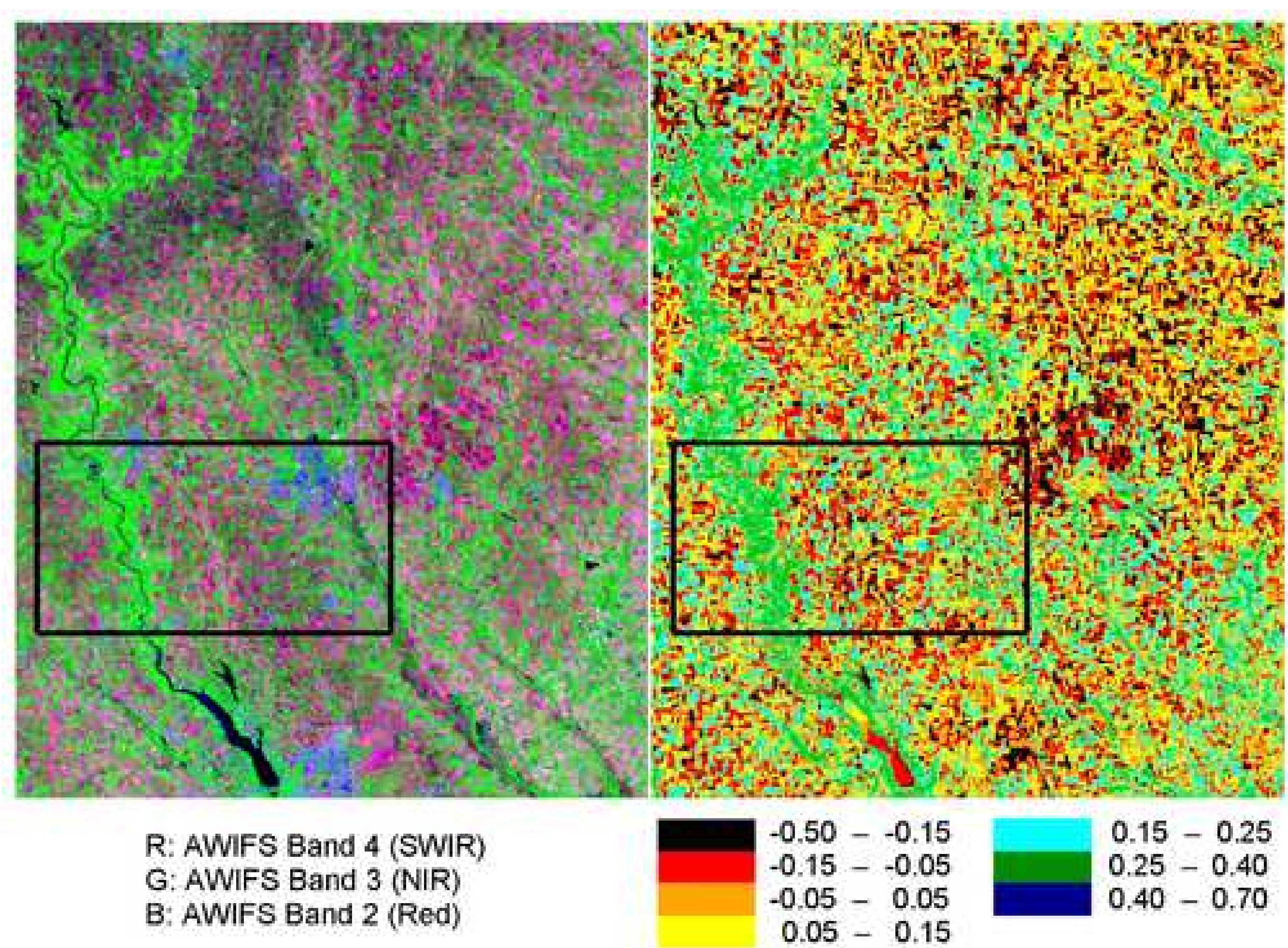

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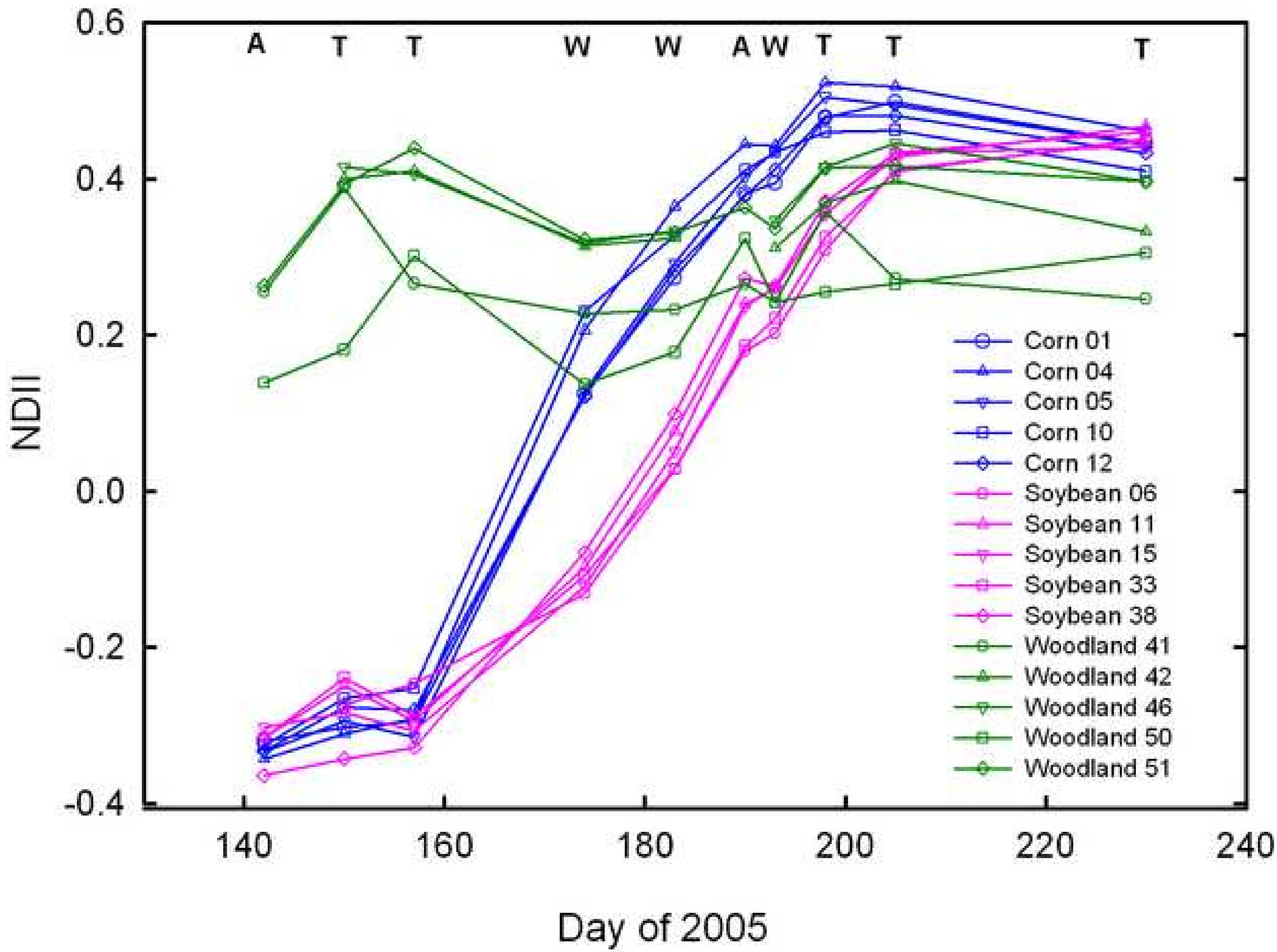

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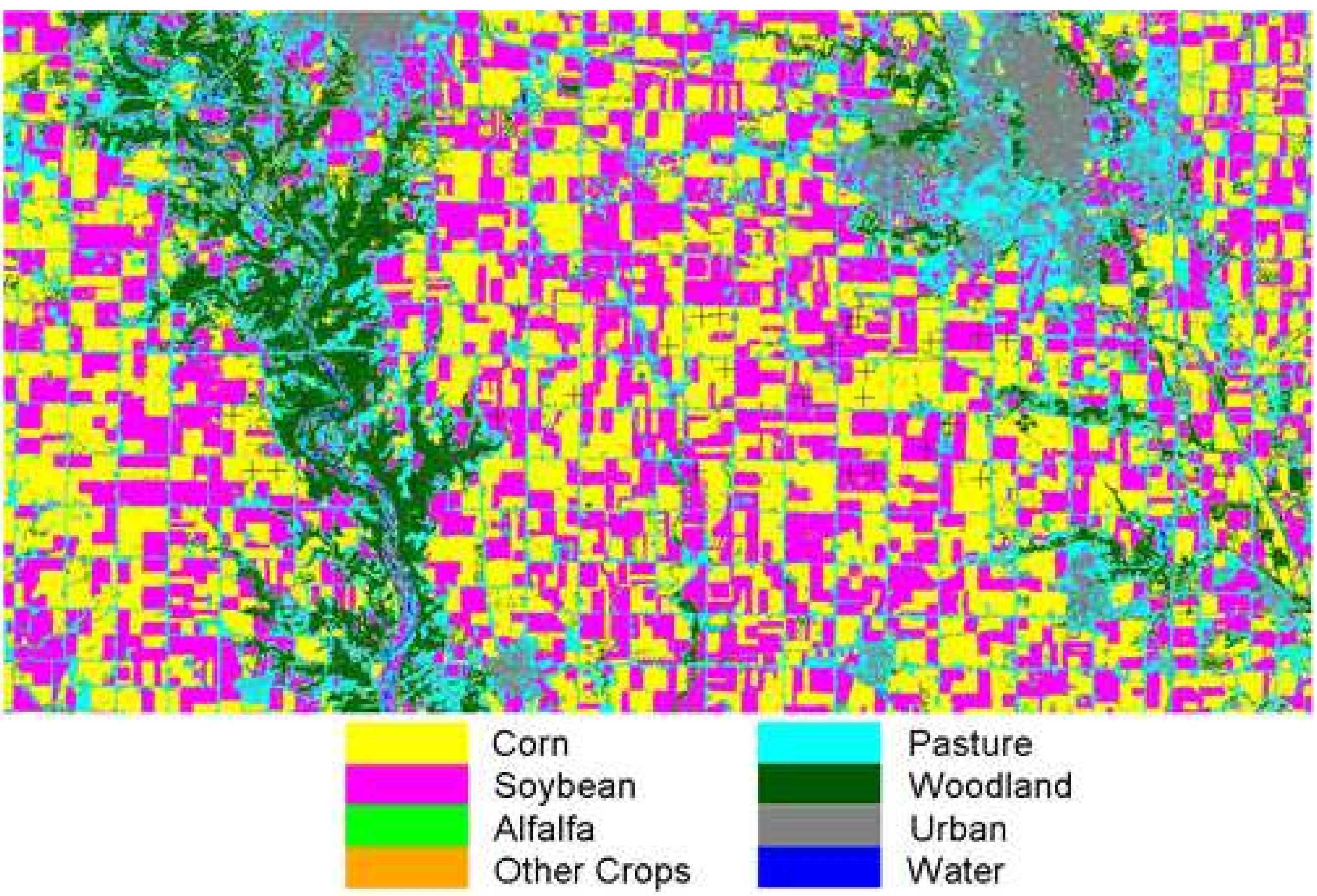

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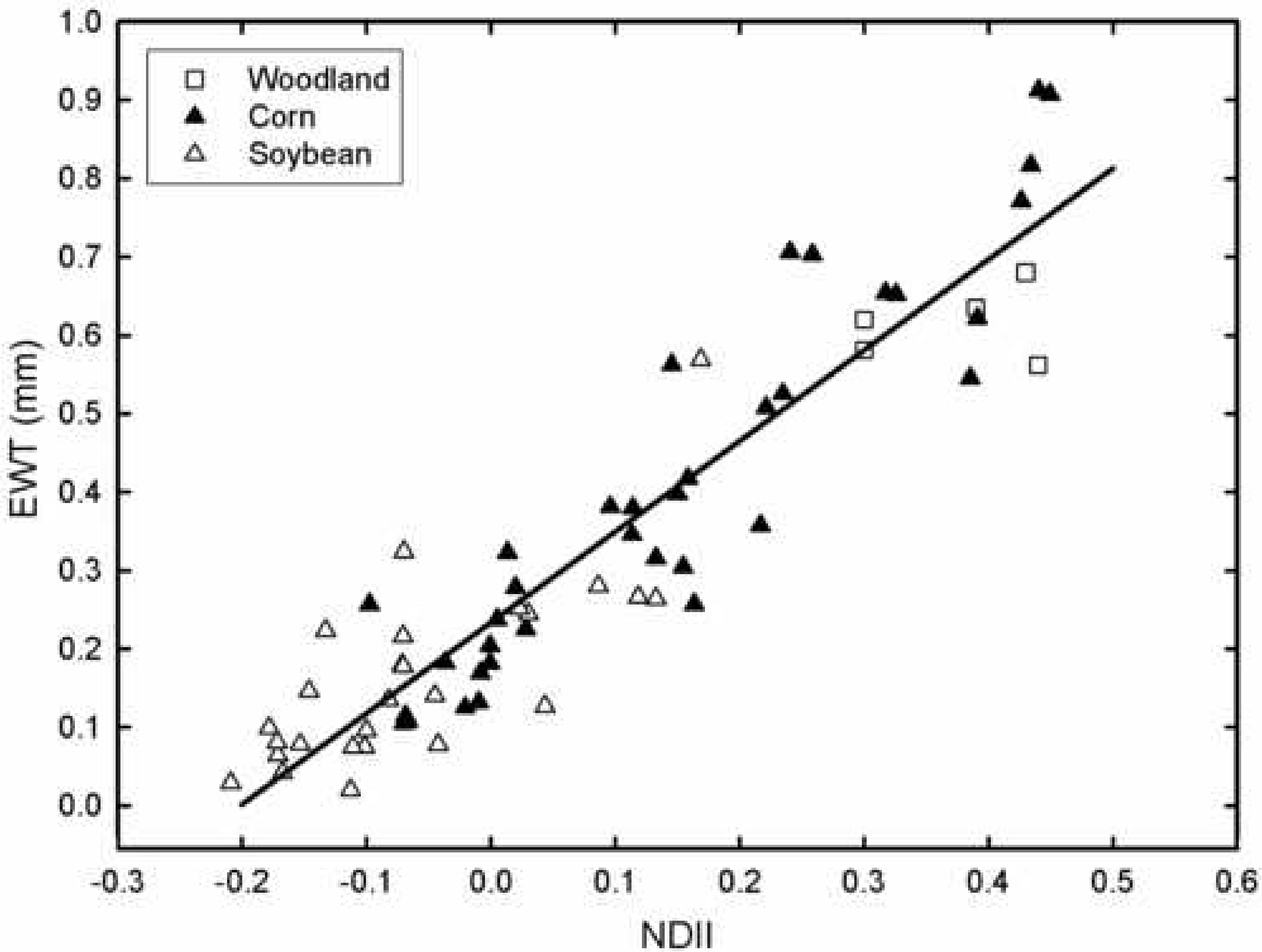

Figure 5

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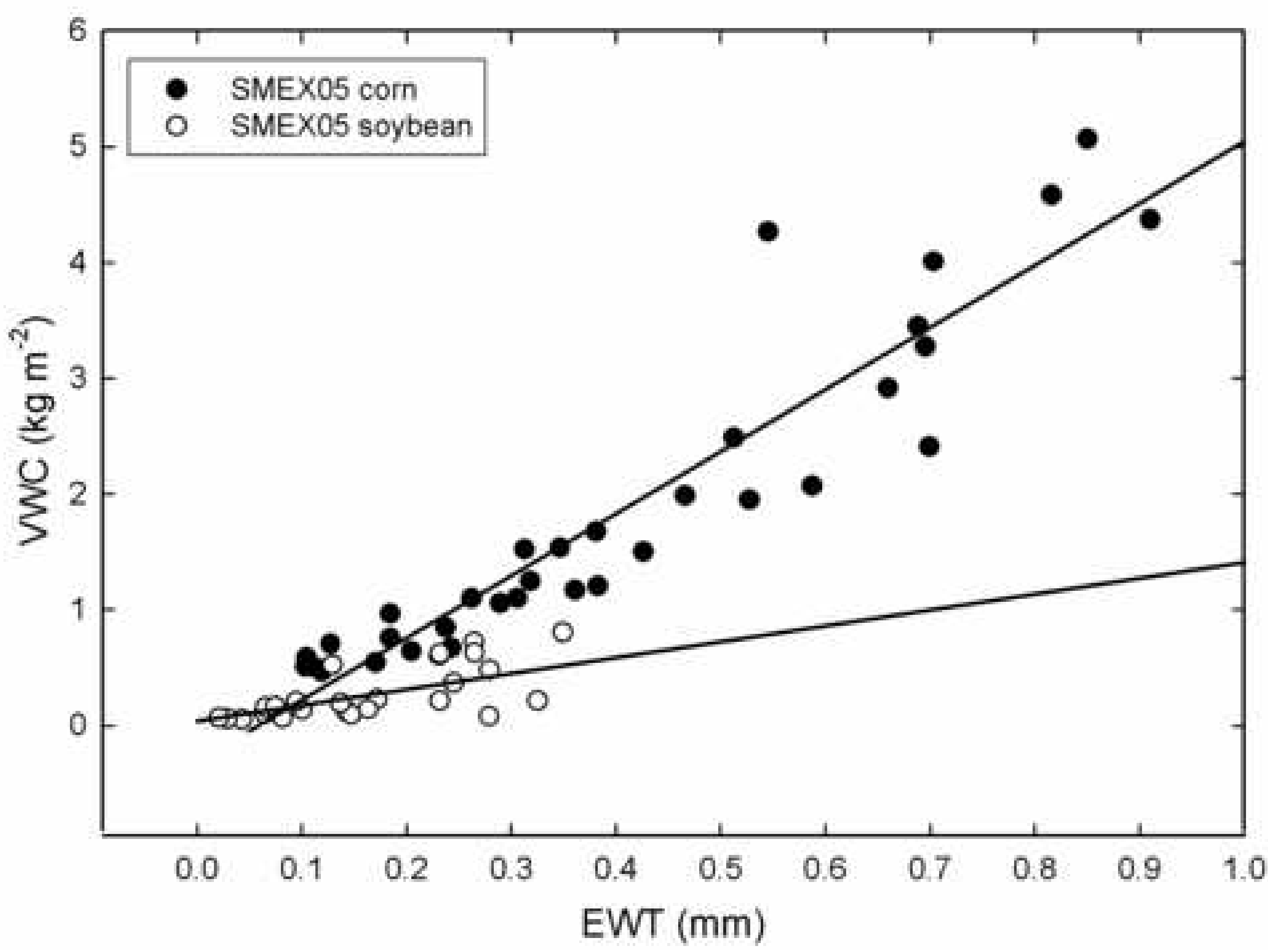

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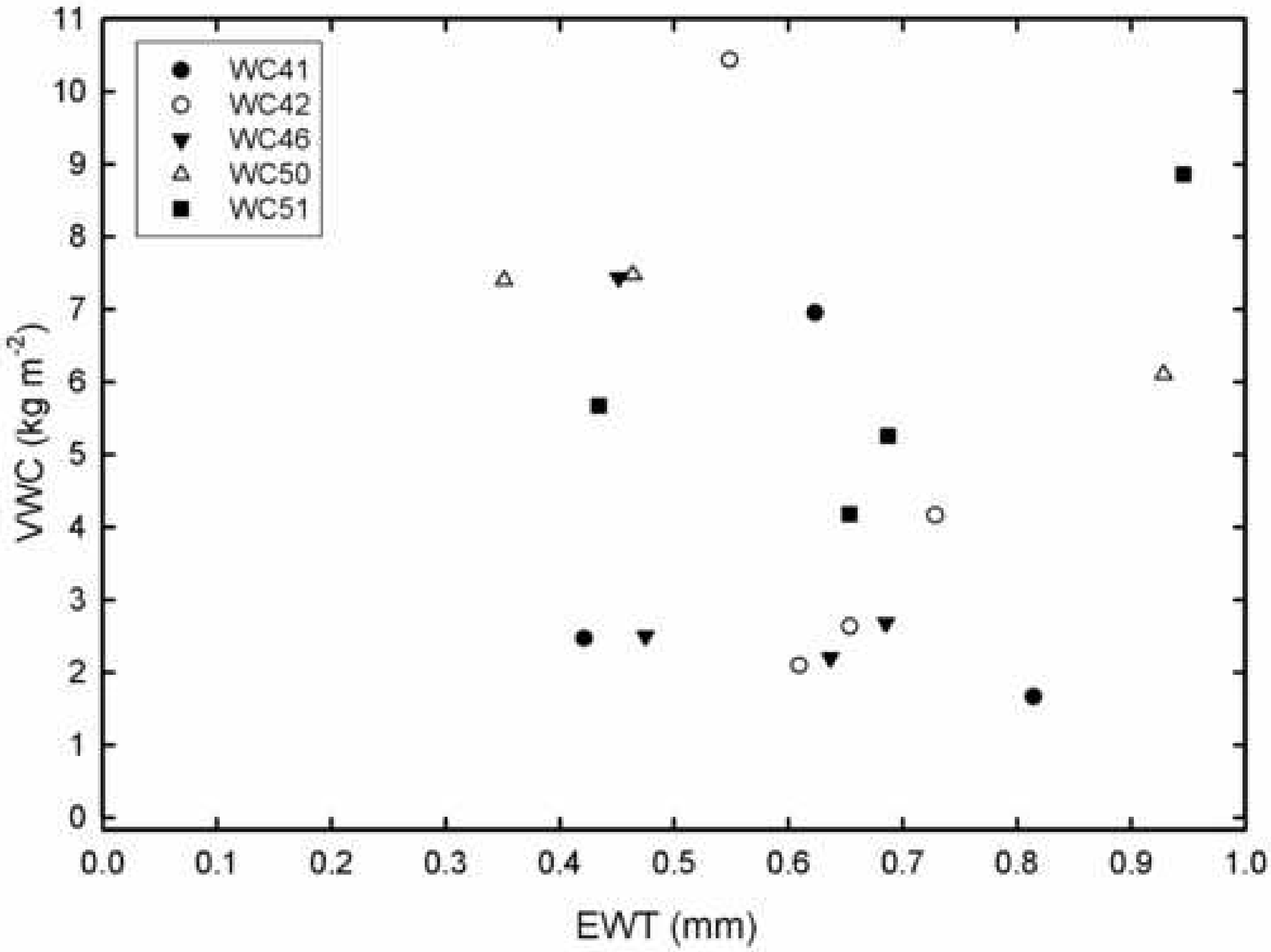

Figure 7

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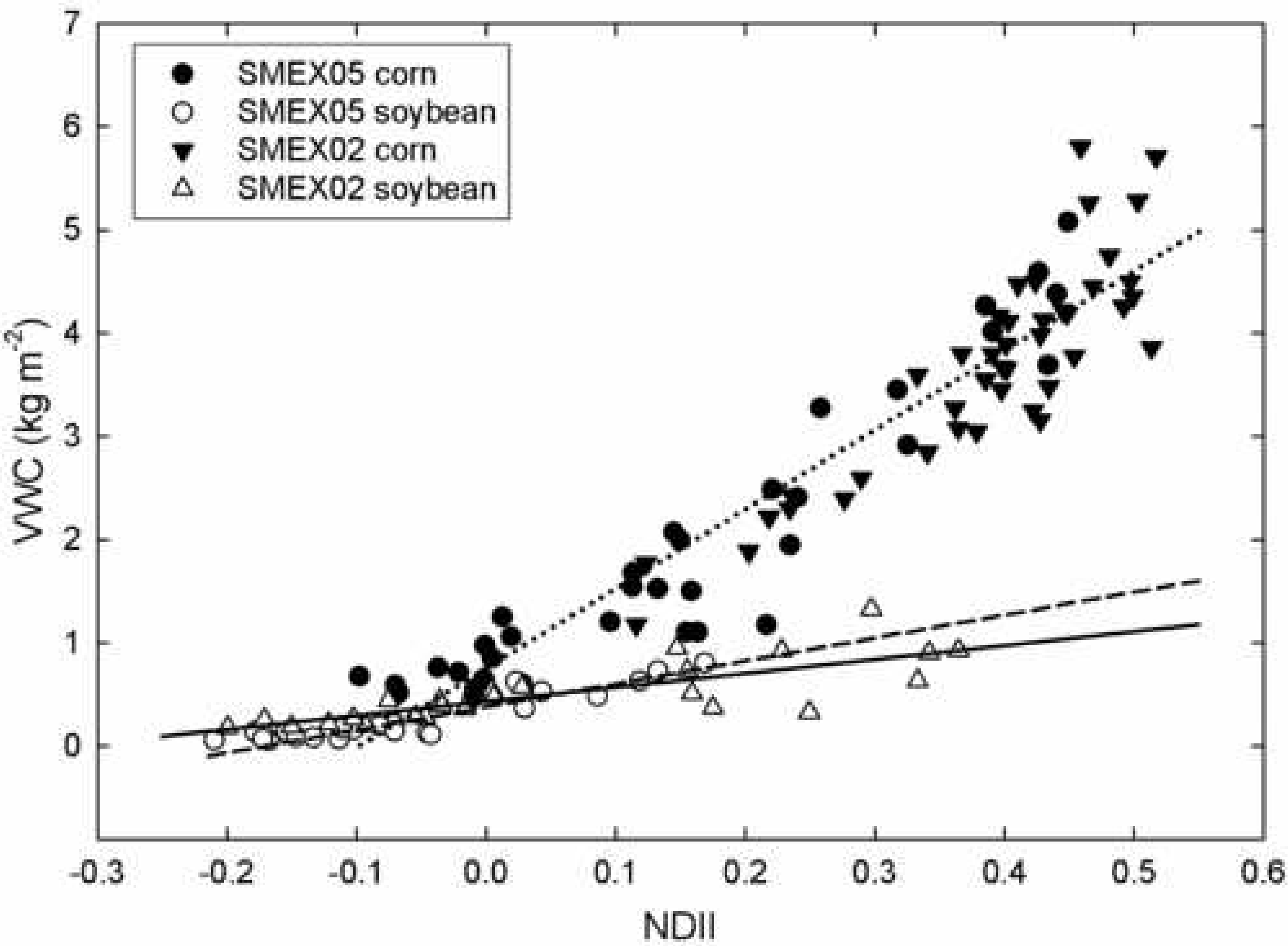

Figure 8
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