# Satellite monitoring of vegetation dynamics: Sensitivity enhancement by the wide dynamic range vegetation index

Andrés Viña
*University of Nebraska at Lincoln*

Geoffrey Henebry
*South Dakota State University*, geoffrey.henebry@sdstate.edu

Anatoly A. Gitelson
*University of Nebraska at Lincoln*, agitelson2@unl.edu

# Satellite monitoring of vegetation dynamics: Sensitivity enhancement by the wide dynamic range vegetation index

Andrés Viña, Geoffrey M. Henebry, and Anatoly A. Gitelson

Center for Advanced Land Management Information Technologies (CALMIT), School of Natural Resources, University of Nebraska-Lincoln, Lincoln, Nebraska, USA

Received 9 November 2003; revised 6 January 2004; accepted 15 January 2004; published 24 February 2004.

[1] Synoptic monitoring of vegetation dynamics relies on satellite observations of the distinctive spectral contrast between red and near infrared reflectance that photosynthetically active green vegetation exhibits. It has long been recognized that the Normalized Difference Vegetation Index (NDVI) suffers a rapid decrease of sensitivity at moderate-to-high densities of photosynthetic green biomass. This decrease can conceal detection of vegetation change in croplands, woodlands, and productive grasslands. We applied a recent, straightforward modification of the NDVI, the Wide Dynamic Range Vegetation Index (WDRVI), to a standard AVHRR dataset to assess its sensitivity to variability within ecoregions and across years, relative to NDVI. In productive ecoregions, the sensitivity increased within a single year by up to 47% and the sensitivity to interannual variability increased by up to 100%. The WDRVI exhibited no increase in sensitivity in ecoregions with sparse vegetation. These findings have significant implications for diverse applications of vegetation monitoring products. *INDEX TERMS:* 1640 Global Change: Remote sensing; 1694 Global Change: Instruments and techniques; 1699 Global Change: General or miscellaneous; 9820 General or Miscellaneous: Techniques applicable in three or more fields; 9350 Information Related to Geographic Region: North America. **Citation:** Viña, A., G. M. Henebry, and A. A. Gitelson (2004), Satellite monitoring of vegetation dynamics: Sensitivity enhancement by the wide dynamic range vegetation index, *Geophys. Res. Lett.*, *31*, L04503, doi:10.1029/2003GL019034.

## 1. Introduction

[2] The study of vegetation dynamics at continental to global scales was enabled in 1979 by the Advanced Very High Resolution Radiometer (AVHRR) onboard National Oceanic and Atmospheric Administration (NOAA) Polar-orbiting Operational Environmental Satellites [POES; *Justice et al.*, 1985; *Tucker et al.*, 1985; *Eidenshink*, 1992]. These sensors gather daily images of the earth at a nominal spatial resolution of 1.1 km. Vegetation monitoring and mapping using AVHRR data has relied on the Normalized Difference Vegetation Index (NDVI) derived from the red and near-infrared (NIR) channels of the AVHRR series [*Ehrlich et al.*, 1994]. Although this index has a solid theoretical basis as a measure of the absorbed photosynthetically active radiation [*Sellers*, 1985], several authors have pointed out limitations due to choices of band location and bandwidth [e.g., *Yoder and Waring*, 1994; *Gitelson et al.*, 1996] and the saturation of red reflectance at high values of chlorophyll content, percent canopy cover and/or Leaf Area Index [e.g., *Kanemasu*, 1974; *Buschmann and Nagel*, 1993]. Consequently, the NDVI approaches an asymptotic saturation under conditions of moderate to high green biomass [e.g., *Sellers*, 1985; *Baret and Guyot*, 1991; *Jenkins et al.*, 2002; *Gitelson et al.*, 2003], which conceals changes in biophysical characteristics of woodlands, croplands, and productive grasslands with moderate to high biomass density.

[3] Alternative methods have been proposed that yield more linear relationships between remotely sensed data and percent canopy cover, leaf area index, and green biomass [e.g., *Chen and Cihlar*, 1996; *Gao et al.*, 2000; *Gitelson et al.*, 2003]; however, these require spectral channels that are not available on the AVHRR, making them not suitable for correcting the historical archive.

[4] Here we evaluate the efficiency of a recently proposed modification to the NDVI, the Wide Dynamic Range Vegetation Index [WDRVI; *Gitelson*, 2004], to overcome the decreased NDVI sensitivity at moderate to high densities of green biomass.

## 2. Methods

### 2.1. Study Area and Data

[5] We used a time series (1995–2000) of biweekly composite images, acquired by the AVHRR sensor onboard the NOAA-14 satellite for the conterminous United States (CONUS) produced by the USGS Earth Resources Observation System Data Center. A biweekly composite image represents a mosaic of maximal NDVI observations acquired during a 14-day period, resulting in a single image that is less affected by obscuring cloud cover [*Holben*, 1986; *Eidenshink*, 1992].

### 2.2. Wide Dynamic Range Vegetation Index

[6] A new approach to improve the vegetation index sensitivity under moderate to high densities of green biomass has been recently proposed and demonstrated with close range sensing of wheat, corn, and soybean canopies [*Gitelson*, 2004]. We applied this approach to the image time series to evaluate whether it could provide improved sensitivity over productive vegetated surfaces relative to the AVHRR-NDVI. Vegetation indices (VI) were calculated from red and near-infrared AVHRR Top-of-Atmosphere (TOA) reflectance as [*Gitelson*, 2004]:

$$\mathrm{VI} = (\alpha * \mathrm{NIR} - \mathrm{red})/(\alpha * \mathrm{NIR} + \mathrm{red}) \tag{1}$$

where $\alpha$ is a weighting coefficient. When $\alpha = 1$, the equation yields the conventional NDVI formulation


0094-8276/04/2003GL019034$05.00

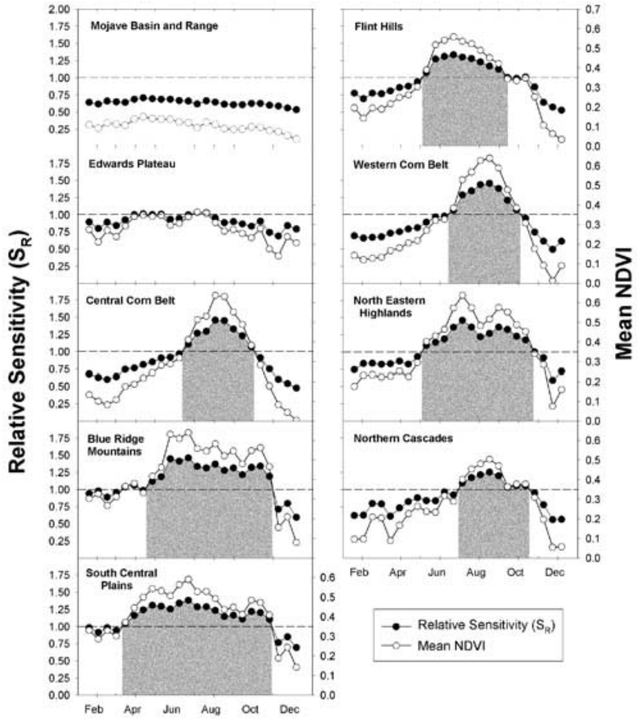


**Figure 1.** Temporal profiles of relative sensitivity ($S_r$) and the mean NDVI for selected U.S. ecoregions. Dotted line represents the point at which the sensitivity to changes in vegetation is equivalent in both the NDVI and the WDRVI (i.e., $S_r = 1$). $S_r < 1$ indicates that the NDVI is more sensitive than the WDRVI; $S_r > 1$ indicates that the sensitivity of the WDRVI is higher (shaded areas). The transition from $S_r < 1$ to $S_r > 1$ occurs near NDVI values of around 0.35.

[*Rouse et al.*, 1974]; when $0 < \alpha < 1$, the equation yields the WDRVI. With $\alpha < 1$, the contribution from the NIR channel is attenuated, making it more comparable to the red channel values. This is particularly important under conditions of moderate to high densities of green biomass, when NIR reflectance is significantly higher than that of red. The specific magnitude of $\alpha$ depends primarily on sensor characteristics, atmospheric conditions and on vegetation amount and type. Values between 0.05 and 0.2 have been found to be effective for proximal sensing of LAI and vegetation fraction in row crops [*Gitelson*, 2004]. In our calculations, $\alpha = 0.2$ was selected due to atmospheric effects, which tend to increase radiance in the red channel and sometimes lessen it in the NIR channel [*Kaufman*, 1989].

### 2.3. Ecoregion Selection

[7] Ecoregions are large areas that contain geographically distinct assemblages of biota, sharing a large majority of their species, dynamics, and environmental conditions [*Omernik*, 1987]. We selected nine ecoregions within CONUS that represent a wide range of vegetation types and phenological cycles (Figures 1 and 2), in order to evaluate the sensitivities of the NDVI and the WDRVI during the growing season of 2000. The specific Omernik Level III ecoregions selected were: Mojave Basin and Range (Ecoregion #13), Flint Hills (#28), Edwards Plateau (#30), South Central Plains (#35), Western Corn Belt Plains (#47), Central Corn Belt Plains (#54), Northeastern Highlands (#58), Blue Ridge Mountains (#66), and Northern Cascades (#77).

### 2.4. Sensitivity Analysis

[8] The sensitivity to intraregional (i.e., within ecoregions) changes in vegetation status of the WDRVI relative to that of the NDVI, $S_r$, was compared quantitatively for each of the nine ecoregions selected during the 2000 growing season, using the following expression [*Gitelson*, 2004]:

$$S_r = (dWDRVI/dNDVI) * (\Delta NDVI/\Delta WDRVI) \tag{2}$$

where dWDRVI/dNDVI is the first derivative of the function WDRVI vs. NDVI, and ΔWDRVI and ΔNDVI are the index ranges, i.e., the differences between the maximal and minimal index values observed during the growing season. Values of $S_r < 1$ indicate situations in which the NDVI is more sensitive than the WDRVI to changes in vegetation status. When $S_r = 1$, the sensitivities of the indices are equivalent. Values of $S_r > 1$ indicate that the WDRVI is more sensitive than the NDVI.

[9] The same sensitivity analysis was performed to assess the interannual variation at each pixel location in the 1995–2000 image time series. To maximize phenological differences in the vegetation, we used the AVHRR NDVI composites for spring (April), summer (August), and autumn (October).

## 3. Results and Discussion

[10] Marked differences in the NDVI occur between ecoregions. Those characterized by sparse vegetation, e.g., Mojave Basin and Range, and Edwards Plateau, exhibited only minor seasonal variations in the NDVI (Figure 1). The other, well-vegetated ecoregions exhibited substantial NDVI seasonality.

[11] Analysis of the intraregional sensitivity, performed on ecoregions with low, intermediate and high green biomass, shows that $S_r$ remains below 1.0 during the entire year

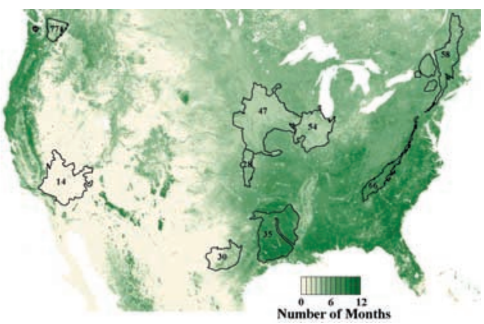


**Figure 2.** Number of months in 2000 in which AVHRR NDVI values exceeded 0.35, a threshold value established to represent the point at which top-of-atmosphere (TOA) NDVI begins to exhibit a significant decrease in sensitivity to changes in vegetation density. The map represents both the location and the persistence of the reduction in the information content of historical AVHRR NDVI data. Polygons delimited in black represent the nine *Omernik* [1987] ecoregions selected.

**Table 1.** Persistence of the Enhanced Sensitivity of the WDRVI During 2000

| Ecoregion Name (Number) | Max NDVI | NDVI at Rising Cross-Over | NDVI at Falling Cross-Over | Persistence of Enhanced WDRVI Sensitivity (% of year) |
|---|---|---|---|---|
| Flint Hills (28) | 0.55 | 0.38 | 0.38 | 33 |
| South Central Plains (35) | 0.58 | 0.40 | 0.41 | 59 |
| Western Corn Belt (47) | 0.63 | 0.33 | 0.36 | 31 |
| Central Corn Belt (54) | 0.63 | 0.34 | 0.38 | 30 |
| North Eastern Highlands (58) | 0.63 | 0.40 | 0.41 | 44 |
| Blue Ridge Mountains (66) | 0.63 | 0.38 | 0.35 | 53 |
| Northern Cascades (77) | 0.50 | 0.40 | 0.38 | 18 |

in ecoregions with low productivity, viz., Mojave Basin and Edwards Plateau (Figure 1). Thus, the NDVI is demonstrably better for studying land surface dynamics in arid to semi-arid environments. When the density of green vegetation is in an intermediate range ($0.3 < \text{NDVI} < 0.4$), both indices exhibit a comparable sensitivity to changes in vegetation ($S_r \approx 1$). In contrast, in situations with dense green aboveground biomass ($\text{NDVI} > 0.4$), the sensitivity of the WDRVI is up to 47% greater than that of the NDVI (Figure 1). This makes the WDRVI a better choice for characterizing vegetated land surface dynamics in woodlands, subhumid to humid grasslands, and croplands.

[12] With the exception of the two ecoregions with low productivity, every ecoregion studied exhibited a period of index crossover, i.e., when the WDRVI displayed greater sensitivity than the NDVI for some portion of the year. The temporal characteristics of the crossover periods vary among ecoregions, e.g., the highly productive South Central Plains ecoregion was in a period of diminished NDVI sensitivity for nearly 60% of the year in contrast to the nearly 20% for the high-altitude, coniferous Northern Cascades (Table 1). NDVI values, however, showed little variation across ecoregions during the time at which the crossovers occur, remaining within 0.33 and 0.41 (Table 1).

[13] It has been reported that the decrease in sensitivity of the NDVI starts to be noticeable at LAI values of around 2, corresponding to NDVI values of around 0.65 for close range sensing, i.e., using top-of-canopy (TOC) reflectances [*Myneni et al.*, 1997; *Gitelson et al.*, 2003]. This threshold value will occur at significantly lower NDVI values when using the top-of-atmosphere (TOA) reflectances that are measured by spaceborne sensors, such as the AVHRR. The differences between TOC-NDVI and TOA-NDVI have been observed to range from 0.20 to 0.37 for terrestrial vegetation [*Kaufman*, 1989]. Hence, a threshold value for the decrease in sensitivity of the TOA-NDVI is expected to be in the range between 0.3 and 0.4. This range is in accordance with the index cross-over observed in TOA-NDVI (i.e., $S_r \approx 1$; Figure 1, Table 1).

[14] Using a threshold value of 0.35, we mapped the location and persistence of the reduction in TOA-NDVI sensitivity for the conterminous United States (Figure 2). More than 73% of the land surface area of CONUS shows one or more months of reduction in NDVI sensitivity, with more than 20% of the land surface area exhibiting sensitivity reduction for six months or more (Figure 2). Such extensive reductions in NDVI sensitivity reveal the widespread uncertainties in observing vegetation dynamics in areas of moderate to high productivity.

[15] Figure 3 displays the interannual sensitivity analysis for the months of April, August, and October, representing the spring, summer, and autumn seasons. As expected, $S_r$ was consistently less than 1.0 in areas of sparser vegetation, which represents a higher sensitivity of NDVI to temporal variation of vegetation on a per pixel basis in regions such as deserts, shrublands, and semiarid grasslands. In contrast, in moister, more productive areas of CONUS, $S_r$ was generally greater than 1.0, reaching values of up to 2.0, i.e., 100% increase in sensitivity. $S_r$ values less than 1.0

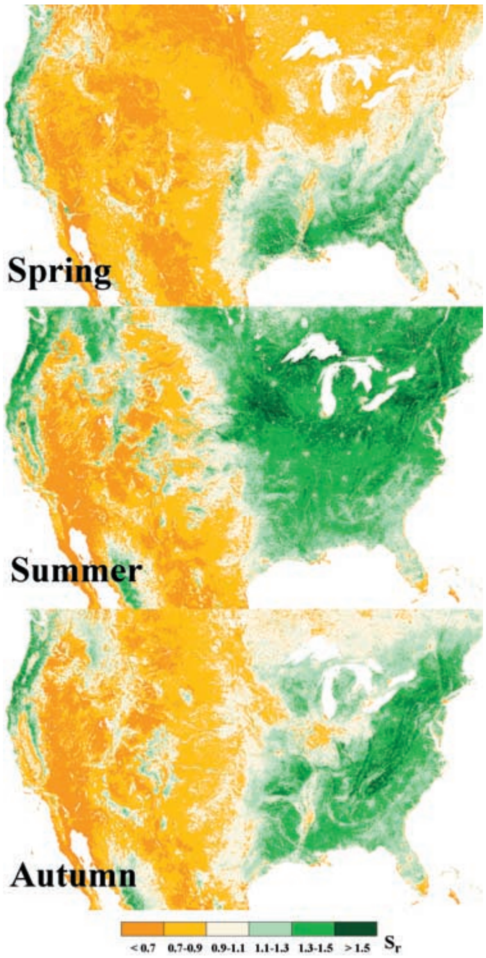


**Figure 3.** Spring (April), summer (August) and autumn (October) maps of the relative sensitivity ($S_r$) to interannual variability of vegetation (1995–2000). The maps represent, on a per pixel basis, the location and magnitude of the differences in the interannual variation detected by the WDRVI and those by the NDVI. Areas depicted in shades of green (yellow) show the regions in which the WDRVI (NDVI) is able to detect more variability than the NDVI (WDRVI).

were observed only during the transitional green-up and brown-down periods.

[16] The presence of spatial and temporal coherence in the differential sensitivities of the indices to interannual variation in vegetation, demonstrates that the WDRVI provides applicable increases in sensitivity compared to the NDVI and, further, that this enhancement is not an augmentation of noise or compositing artifacts found in the dataset [*Moody and Strahler*, 1994].

## 4. Conclusions

[17] We have demonstrated, using a standard AVHRR dataset, that a simple modification of the NDVI can enhance the sensitivity of AVHRR observations of vegetated surfaces with moderate to high densities of green biomass.

[18] A vegetation index that combines the features of the NDVI and those of the WDRVI could be designed using a smoothing function that selects the coefficient $\alpha$ in equation 1 as a function of the density of vegetation. This would require a large set of representative canopy spectral time series to derive the right optimization approach.

[19] The implications of these findings are far-reaching. Diverse regional to global studies requiring synoptic data may benefit from the increased sensitivity available through the WDRVI, used in conjunction with the NDVI, including land surface characterizations for numerical weather prediction models [*Gutman and Ignatov*, 1998], carbon cycle modeling [*Myneni et al.*, 2001], monitoring land cover change [*Skole and Tucker*, 1993], biodiversity mapping [*Scott and Jennings*, 1998], and ecological forecasting [*Clark*, 2003]. The ability to diminish uncertainty in vegetation monitoring signals a new episode in earth observation, one in which the image archives should be revisited for a fresh look that may well lead to new findings.

[20] **Acknowledgments.** We acknowledge the suggestions and comments to the manuscript provided by Giorgio Dall'Olmo. The research was supported in part by grants from the NASA LCLUC program, the NSF Biodiversity and Ecosystem Informatics program, USGS Gap Analysis Program, and U.S. Department of Energy: (a) EPSCoR program, Grant No. DE-FG-02-00ER45827 and (b) Office of Science (BER), Grant No. DE-FG03-00ER62996. A contribution of the University of Nebraska Agricultural Research Division, Lincoln, NE, Journal Series No.14395. This research was also supported in part by funds provided through the Hatch Act.

## References

Baret, F., and G. Guyot (1991), Potentials and limits of vegetation indices for LAI and PAR assessment, *Remote Sens. Environ.*, *35*, 161–173.

Buschmann, C., and E. Nagel (1993), In vivo spectroscopy and internal optics of leaves as basis for remote sensing of vegetation, *Int. J. Remote Sens.*, *14*, 711–722.

Chen, J. M., and J. Cihlar (1996), Retrieving leaf area index of boreal conifer forests using Landsat TM images, *Remote Sens. Environ.*, *55*, 153–162.

Clark, J. S. (2003), Uncertainty in ecological inference and forecasting, *Ecology*, *84*, 1349–1359.

Ehrlich, D., J. E. Estes, and A. Singh (1994), Applications of NOAA-AVHRR 1 km data for environmental monitoring, *Int. J. Remote Sens.*, *15*, 145–161.

Eidenshink, J. C. (1992), The 1990 Conterminous U. S. AVHRR data set, *Photogramm. Eng. Remote Sens.*, *58*, 809–813.

Gao, X., A. R. Huete, W. Ni, and T. Miura (2000), Optical-biophysical relationships of vegetation spectra without background contamination, *Remote Sens. Environ.*, *74*, 609–620.

Gitelson, A. A., Y. J. Kaufman, and M. N. Merzlyak (1996), Use of green channel in remote sensing of global vegetation from EOS-MODIS, *Remote Sens. Environ.*, *58*, 289–298.

Gitelson, A. A., A. Viña, T. J. Arkebauer, D. C. Rundquist, G. Keydan, and B. Leavitt (2003), Remote estimation of leaf area index and green leaf biomass in maize canopies, *Geophys. Res. Lett.*, *30*(5), 1248, doi:10.1029/2002GL016450.

Gitelson, A. A. (2004), Wide Dynamic Range Vegetation Index for remote quantification of biophysical characteristics of vegetation, *J. Plant Physiol.*, *161*, 165–173.

Gutman, G., and A. Ignatov (1998), Derivation of green vegetation fraction from NOAA/AVHRR for use in numerical weather prediction models, *Int. J. Remote Sens.*, *19*, 1533–1543.

Holben, B. N. (1986), Characteristics of maximum-value composite images from temporal AVHRR data, *Int. J. Remote Sens.*, *23*, 1417–1434.

Jenkins, J. P., B. H. Braswell, S. E. Frolking, and J. D. Aber (2002), Detecting and predicting spatial and interannual patterns of temperate forest springtime phenology in the eastern U.S., *Geophys. Res. Lett.*, *29*(24), 2201, doi:10.1029/2001GL014008.

Justice, C. O., J. R. G. Townshend, B. N. Holben, and C. J. Tucker (1985), Analysis of the phenology of global vegetation using meteorological satellite data, *Int. J. Remote Sens.*, *6*, 1271–1318.

Kanemasu, E. T. (1974), Seasonal canopy reflectance patterns of wheat, sorghum, and soybean, *Remote Sens. Environ.*, *3*, 43–47.

Kaufman, Y. J. (1989), The atmospheric effect on remote sensing and its correction, in Theory and applications of optical remote sensing, edited by G. Asrar, John Wiley & Sons, Inc., New York, pp. 336–428.

Moody, A., and A. H. Strahler (1994), Characteristics of composited AVHRR data and problems in their classification, *Int. J. Remote Sens.*, *15*, 3473–3491.

Myneni, R. B., J. Dong, C. J. Tucker, R. K. Kaufmann, P. E. Kauppi, J. Liski, L. Zhou, V. Lexeyev, and M. K. Hughes (2001), A large carbon sink in the woody biomass of Northern forests, *Proceedings of the National Academy of Science*, *98*, 14,784–14,789.

Myneni, R. B., R. R. Nemani, and S. W. Running (1997), Estimation of global leaf area index and absorbed PAR using radiative transfer models, *IEEE Trans. Geosci. Remote Sens.*, *35*, 1380–1393.

Omernik, J. M. (1987), Ecoregions of the conterminous United States, Map scale 1:7,500,000, *Annals of the Association of American Geographers*, *77*, 118–125.

Rouse, J. W., R. H. Haas Jr., J. A. Schell, and D. W. Deering (1974), Monitoring vegetation systems in the Great Plains with ERTS, NASA SP-351, Third ERTS-1 Symposium, Vol. 1, pp. 309–317, NASA, Washington, D.C.

Scott, J. M., and M. D. Jennings (1998), Large area mapping of biodiversity, *Annals of the Missouri Botanical Garden*, *85*, 34–47.

Sellers, P. J. (1985), Canopy reflectance, photosynthesis and transpiration, *Intl. J. Remote Sens.*, *6*, 1335–1372.

Skole, D., and C. Tucker (1993), Tropical deforestation and habitat fragmentation in the Amazon: Satellite data from 1978 to 1988, *Science*, *260*, 1905–1910.

Tucker, C. J., J. R. G. Townshend, and T. E. Goff (1985), African land-cover classification using satellite data, *Science*, *227*, 369–375.

Yoder, B. J., and R. H. Waring (1994), The normalized difference vegetation index of small Douglas-Fir canopies with varying chlorophyll concentrations, *Remote Sens. Environ.*, *48*, 81–91.

A. Viña, G. M. Henebry, and A. A. Gitelson, Center for Advanced Land Management Information Technologies (CALMIT), School of Natural Resources, University of Nebraska-Lincoln, 102 East Nebraska Hall, Lincoln, NE 68588-0517, USA. (avina@calmit.unl.edu)