CHARACTERIZING LAI SPATIAL AND TEMPORAL VARIABILITY USING A WAVELET APPROACH

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ABSTRACT:

Vegetation plays an important role in the exchange of carbon dioxide, water, and energy between the land surface and the atmosphere. LAI, defined as one-half the total green leaf area per unit of ground surface area, drives the within and the below canopy microclimate, determines canopy water interception, radiation extinction, and water and carbon gas exchange. Therefore, accurate LAI is a key parameter in all models describing the exchange of fluxes of energy, mass (e.g., water and CO_2), and momentum between the surface and the planetary boundary layer. Unfortunately, LAI is very difficult to quantify accurately due to its spatial heterogeneity and temporal dynamics. The long-term objectives of this study are 1) to improve LAI estimation accuracy with considerations of scale, heterogeneity (spatial, vertical, and temporal), and land cover type, 2) to develop a better approach to LAI parameterization for models in hydrology, climatology, and ecosystem, and 3) to investigate the effects of land cover and land use changes on LAI dynamics, which can cause massive hydrological change. In this paper, we aim to 1) characterize the spatial scale of LAI and normalized difference of vegetation index (NDVI) in a Canadian prairie using a wavelet approach based on field measured LAI and reflectance data, and 2) to simulate the temporal dynamics of LAI variation intra-annually with both ground measured LAI and satellite derived NDVI values. The study area is in St. Denis Wildlife Reserve Area, 40km east of Saskatoon, Saskatchewan, Canada. Results indicated that the spatial variation of LAI and NDVI is maximized at 22.5 meters and with several small scale variations (4.5m, 12m, and 18m). The temporal LAI dynamics indicated that the native prairie greens up in May and senescent in September, and the maximum growing season is in July for the Canadian prairie.

1. INTRODUCTION

Vegetation plays an important role in the exchange of carbon dioxide, water, and energy between the land surface and the atmosphere. LAI, defined as one-half the total green leaf area per unit of ground surface area (Chen & Black, 1992), drives the within and the below canopy microclimate, determines canopy water interception, radiation extinction, and water and carbon gas exchange. Therefore, LAI is a key parameter in all models describing the exchange of fluxes of energy, mass (e.g., water and CO_2), and momentum between the surface and the planetary boundary layer (Knyazikhin, et al., 1998).

LAI has been selected in a broad range of models including vegetation (Moulin et al., 1998, Cayrol et al., 2000), biogeochemical (Running et al., 1999), hydrological (Andersen *et al*.., 2002), and global atmospheric circulation (Avissar & Chen, 1993). Some popular examples of these models are BEPS (Liu *et al.,* 1997), BGC (Kimball *et al.*, 1997), CENTURY (Parton et al., 1988), TEM (McGuire *et al*., 1997), CLASS (*Verseghy,* 1993), CHRM (Pomeroy *et al*., 2006), NCAR CCM (Chase et al, 1996), AGCMs (Krinner et al., 2005), and MM5 (Grell, et al., 1994). Currently, these models are initiated by either field validation of simulated LAI or remotely sensed estimates of LAI (Running et al., 1999). However, many climate and ecosystem models are very sensitive to variation in LAI (Bonan, 1993) and thus rely on accurate LAI estimates. For example, the Global Climate Observation System (GCOS) and the Global Terrestrial Observation System (GTOS) requires an LAI accuracy of 0.2 to 1.0 for terrestrial climate modeling. Unfortunately, LAI is very difficult to quantify accurately, due to its spatial (horizontal and vertical) and temporal variability, as annual cycles and interannual variability interact with the vegetation structure, stratification and heterogeneity.

Currently, there are three major methods for obtaining LAI estimations: ground measurement, remote sensing derivation, and hybrid approaches. The major ground-based methodologies employ either "direct" measures (involving destructive sampling, litterfall collection, or point contact sampling) or "indirect" methods (involving optical instruments and models). While accurate on a per plant or site basis, direct methods are time consuming and tedious (Lang et al., 1985) and destructive to plants. A review of the direct LAI measurement techniques is given in Norman and Campbell (1989). By contrast, indirect optical methods hold great promise because of the potential to obtain quick and low-cost measurements over large areas. However, several commercial optical instruments, including the LAI-2000 plant canopy analyzer (LI-COR, Lincoln, Nebraska) and Sunfleck Ceptometer (Decagon Devices, Pullman, Washington), are hindered by the complexity of natural canopy architecture. Most studies concluded that indirect methods underestimated LAI when compared with direct measurements (Chason *et al*., 1991; Comeau *et al*., 1998). The reported underestimation varies from 25% to 50% in different stands (Gower and Norman, 1991; Gower *et al*., 1999). The degree of error in the LAI measurement is a result of the canopy's deviation from the assumption of random dispersion, which was

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named 'clumping' (Chen *et al*., 1997). Many solutions have been proposed to overcome this clumping bias. For example, two new instruments have been developed to measure the between-shoot clumping factor (Ω_e): the TRAC developed by Chen *et al*. (1997) and the MVI developed by Kucharik *et al*. (1997). Furthermore, the boundary and illumination conditions, data aggregation method, and sampling scheme also influence the relative accuracy of LAI measurements. Even though hemispherical photography was believed better than LAI-2000, it is more suitable for trees instead of prairie regions with low canopy vegetation.

Although LAI can be directly or indirectly measured by several ground-based methods, difficulties in deriving it from remotely sensed data has led to the development of various approaches and methodologies (especially for LAI determination at different scales and over diverse types of vegetation canopies) (Baret and Guyot, 1991; Haboudane et al., 2004; etc.). Estimating LAI from remotely sensed optical data can generally be carried out by several methods (Liang, 2003): (1) through the empirical relationship between LAI and vegetation indices (LAI-VI); (2) through the inversion of a radiative transfer (RT) model; (3) the use of look-up tables (LUT), (4) neural networks (NN), and (5) a hybrid approach. Using remotely sensed imagery, LAI can be derived from an empirical or modeled LAI–VI relation. The major limitation of this empirical approach is that there is no single LAI-VI equation (with a set of coefficients) that can be applied to remote sensing images of different surface types. Another limitation of this approach is the sensitivity of VI to non-vegetation related factors such as soil background properties (e.g., Huete, 1989), atmospheric conditions (e.g., Kaufman, 1989), topography (Holben & Justice, 1980), bidirectional nature of surfaces (Deering, 1989), and the most important, the spatial and temporal dynamics of LAI.

Therefore, even though recent research has attempted to improve LAI estimates through a better description and sampling of canopy heterogeneity (vertical and horizontal heterogeneity, clumping, and canopy closure or gaps), quantifying LAI with high accuracy presents numerous challenges due to the complex spatial and temporal LAI variations. Satellite imagery has provided promising results. Therefore, this study will investigate the spatial and temporal variations of LAI as well as from the measurement of NDVI.

2. METHODOLOGY

2.1 Study Area

The study area is in St. Denis Wildlife Reserve Area, 40km east of Saskatoon, Saskatchewan, Canada. The study area is dominated by rolling landscapes in the mixed-grass prairie ecodistrict. St. Denis National Wildlife Area has over 200 temporary and permanent wetlands most of which are fringed by tall grass and shrubs. Blocks of native grassland and aspen bluffs with willow, serviceberry and chokecherry are distributed throughout the Wildlife Area. Almost one-half of the previously cultivated land has been seeded to bromegrass and alfalfa for nesting cover. The relatively large amount of existing cultivated land is used for research on the effects of agricultural practices on waterfowl production.

2.2 Field Data Collection and Satellite Imagery Acquisition

Field data were collected along one transect with 128 samples with 4.5m interval three time during the growing season of 2007. Variables collected include LAI with LAI-2000 plant canopy analyzer, reflectance with ASD handheld spectraradiometer, estimated cover, and digital pictures. SPOT 4 multi-spectral 20m resolution imagery was acquired at monthly interval in the summer of 2007, which match with field data collection. Five SPOT scenes were from May, June, July, August, and September respectively. Images were geometrically, radiometrically, and atmospherically corrected. Normalized Difference Vegetation Index (NDVI) was calculated and LAI values were derived from the satellite imagery.

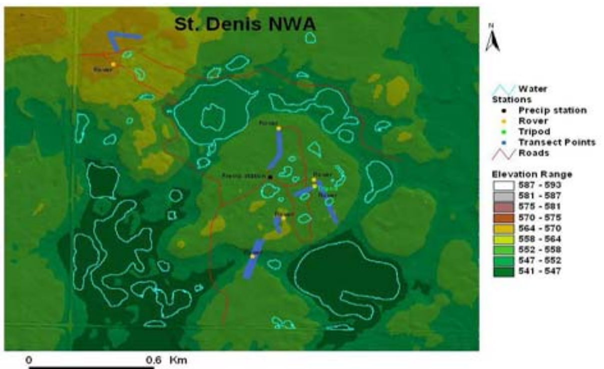


Figure 1. Study area: St. Denis, Saskatchewan, Canada.

2.3 Data Analysis

Normalized difference vegetation index (NDVI) was derived from ground measured reflectance and SPOT satellite imagery. NDVI was calculated based on the ratio of the difference between near infrared and the sum of these two bands.

Wavelet analysis was performed on LAI and NDVI derived from ground measurements in July as this is the maximum growing season in Canadian prairies.

3. RESULTS

3.1 Spatial Variation of LAI and NDVI

Wavelet analysis indicated that LAI has several levels of variations: 4.5m, 12m, and 22.5m. NDVI spatial variation was mostly corresponding with LAI. The variations are at 4.5m, 12m, 18m, and 22.5m. Clearly, the 18m variation from NDVI was not found from LAI, indicating that LAI is not the reason for the variation on NDVI. It might caused by topography (He et al., 2007). Future analysis is necessary.

3.2 Temporal variation of LAI and NDVI

Figure 3 demonstrates the temporal change of the study area. July is the maximum growing season for Canadian prairies. Vegetation greens up in May and senescent in September. The SPOT images are in standard false color composite (RGB: Near infrared, Red, and Green). Different tone of red indicates healthy and dense vegetation, while blue/green is bare ground.

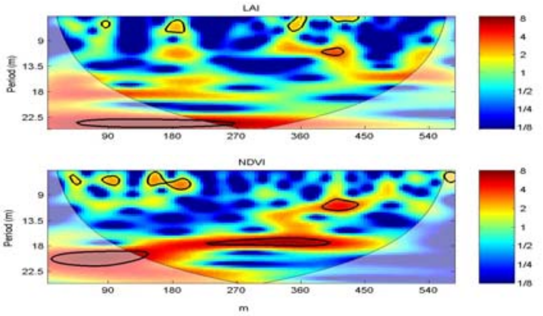


Figure 2. Wavelet analysis results on LAI (top) and NDVI (bottom) along the transect in July. Dark warm color represents higher variation and solid lines are the positive results of significant tests.

Ground measured LAI showed matching trend with NDVI derived from space. Both indicated that the maximum growing season is July with maximum LAI and NDVI values (Figure 4). Figure 4 also showed that tamed grassland (smooth brome) has higher NDVI values and the maximum NDVI appeared later comparing to native prairies.

4. CONCLUSIONS

This study indicated the dynamic spatial and temporal variations of LAI and NDVI in a Canadian Prairie. Spatially, LAI has several levels of variations from small scale to large scale, which can be controlled by different factors. NDVI from remote sensing data can be used to represent the LAI variation at several scales. The maximum growing season for the study area is July for native prairies, but it is delayed to August for tamed grassland.

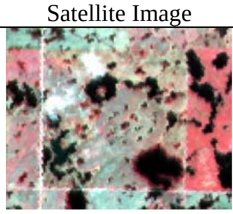
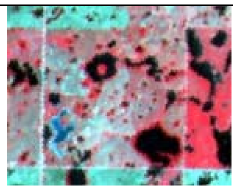
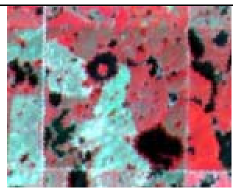
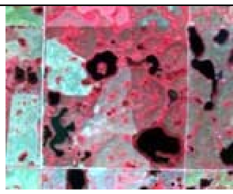
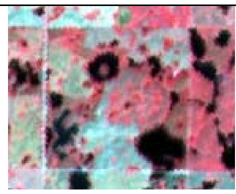
	Picture	Satellite Image
May		
June		
July		
Aug.		
Sept		

Figure 3. Temporal change of the study area from both ground and satellite views.

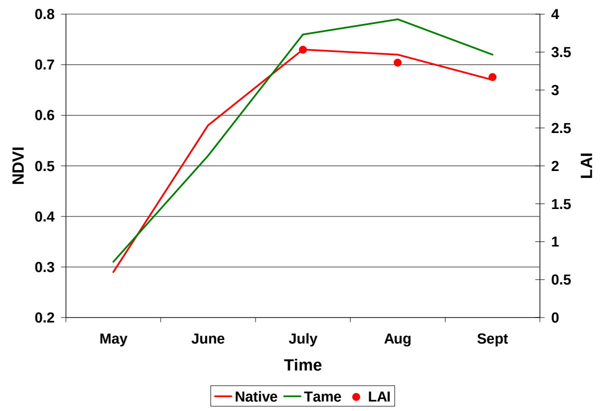


Figure 4. Quantitative measurements of LAI from ground for native prairies (red dots) and NDVI for two grassland types from SPOT satellite imagery for native prairie (red line) and tamed grassland (green line).

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