Remote Sensing of Leaf Area Index (LAI) and a Spatiotemporally Parameterized Model for Mixed Grasslands

Li Shen
Zhaoqin Li
Xulin Guo

Department of Geography and Planning
University of Saskatchewan
Saskatoon, SK S7N5C8, Canada

Abstract

Leaf area index (LAI) is an important biophysical variable used to reflect the vegetation condition in ecosystems. However, accurate estimation of LAI is highly dependent upon the spatiotemporal scales. Both direct (destructive sampling, litter fall collection and point contact sampling) and indirect methods (optical instruments) have been used to measure LAI in mixed grasslands. In particular, remote sensing technique is rapidly gaining wide interest in developing various empirical and physical models for LAI estimation. The present review compares the advantages and disadvantages of different methods in estimating LAI. It also summarizes the spatiotemporal variation of LAI and its sensitive factors. The suitability of remote sensing data in capturing the spatiotemporal variation of LAI is particularly discussed. Based on the gaps found in existing literature, this paper attempts to theoretically propose a spatiotemporally parameterized model to improve the accuracy of LAI derivation in mixed grasslands. The overall objective will be achieved by the following steps:1) Determine the sensitive factors influencing LAI spatiotemporal variation; 2) Identify appropriate remote sensing data in terms of spatial, spectral and temporal resolutions; 3) Establish the LAI parameterized model; 4) Assess the model accuracy and test it in one hydrology model.

Keywords: Leaf Area Index (LAI), mixed grasslands, spatiotemporal variation, remote sensing, parameterized model

1. Introduction

Leaf area index (LAI), defined as half of the total green leaf area per unit of horizontal ground surface, is a critical parameter to quantitatively measure the abundance and structure of vegetation for understanding the entire biophysical processes [1-4]. LAI has wide applications in both agriculture and ecological studies including yield estimation, stress evaluation, primary production related to photosynthesis, respiration, transpiration, carbon and nutrient cycle and rainfall interception [5-6]. Therefore, LAI serves as a necessary input to many agricultural, climatical, ecological and hydrological models such as canopy photosynthesis models, evaporation models, transpiration models, precipitation models, crop growth models and primary production models [3, 7-8]. The performance of these aforementioned models is very sensitive to the variation of LAI at different spatiotemporal scales and requires an accurate estimation of LAI [9].

For mixed grasslands studies, accurate LAI can be a good indicator of the variation of grassland ecosystem dynamics at the landscape level [10-12]. It is easier to obtain accurate *in-situ* LAI using instruments or destructive methods at field sites due to the accessibility and simplicity of vertical dimensions of grasses [13]. For LAI estimation and mapping at different spatiotemporal scales, remote sensing has been considered as a promising tool in quite a few relative studies because of its advantages in large-scale, real-time, and long-term monitoring [14-17]. Particularly most parameterized ecological and hydrological models, for example, the cold region hydrology model (CRHM), require LAI of high accuracy over different spatiotemporal scales to guarantee a better initiation and performance of the model simulation [18].

However, the maximum accuracy of estimated LAI by satellite data can only reach approximately 50% owing to the surface heterogeneity (diverse cover types within a mixed image pixel) as well as the temporal variability of grasslands in different growing seasons [7,9].

Therefore, it is necessary to raise the accuracy of LAI estimation at different spatiotemporal scales to further improve the performance of hydrological and ecological models. In this research, we will establish a spatiotemporal parameterized LAI model combining various sensitive factors using remote sensing approaches. The spatiotemporal scales will be investigated by analyzing both the spatiotemporal resolutions of different satellite imagery and the spatiotemporal variation of LAI in mixed grasslands.

The accuracy of the LAI model will be assessed based on *in-situ* data and then this LAI model will be tested in the cold region hydrology model (CRHM).The following review is organized in four parts for a better understanding of the above proposed objectives. The first one briefly summarizes the current LAI estimation methods. The second one investigates the spatiotemporal variation of LAI and sensitive factors responding to such variation. The third one explored remote sensing of LAI with regard to available sensors, imagery of appropriate temporal, spatial and spectral resolutions for LAI estimation, and current remote sensing models to derive LAI. The final one discusses the importance of LAI dynamic parameterization to the CRHM model for establishing a suitable LAI parameterization scheme of the expected performance of the CRHM model.

2. Methods of LAI Estimation

Two main methods consisting of direct and indirect optical measurements are available for estimating LAI values. Direct methods refer to the ground-based approaches such as destructive sampling, litterfall collection and point contact sampling by completely defoliating green leaves or collecting the leaf litter and then determining LAI in planimetric or gravimetric ways [19]. Jonckheere et al. [20] pointed out that the direct measurement of LAI is the most accurate method. Nevertheless, others argued that this approach is relatively time consuming, labor-intensive, and merely applicable for small plants in limited experimental plots [8, 19, 21].

The limitation of direct methods has been compensated for by indirect methods mainly including LAI optical instruments and satellite sensors which have great potential to estimate LAI over large spatial extents [9, 19]. Common instruments such as LAI-2000 plant canopy analyzer (LI-COR, Lincoln, Nebraska) , SunfleckCeptometer (Decagon Devices, Pullman, Washington) and Demon (Cisro, Center for Environmental Mechanics, Canberra, Australia) are invented relying on the optical transmission theory. Several studies have shown that the primary problem within the instrument-derived measurements is the underestimation of LAI around 25% - 50% [22-24]. This underestimation is caused by the invalidity of the random dispersion in the real canopy as well as experiment designs. To reduce the error of LAI measurements, two new instruments called Tracing Radiation and Architecture of Canopies (TRAC) and MVI were developed by Chen et al. [25] and Kucharik et al. [26] respectively. In contrast, other studies drew different conclusions suggesting that instruments should overestimate LAI since all plant parts are counted as leaf area intercepted [27-28]. The aforementioned field optical instruments with the disadvantages of site-based, time consuming and low frequency fail to estimate LAI over large areas at all scales [21].

Remote sensing as another indirect method holds the greatest potential to characterize LAI variation at different spatiotemporal scales due to the multiple spatiotemporal resolutions of the available satellite data. Besides, remote sensing is considered to be a good solution to the time and labor problems identified in the traditional direct methods [6, 21, 29-30]. Generally, LAI remote sensing inverse models can be classified into three categories. The first type is called the empirical-based model through establishing the relationship between vegetation indices (VIs) and the *in-situ* LAI, which enables the deriving of LAI for large areas by computing the simple statistical equations with remotely sensed VIs as the input. The second type is the radiative transfer (RT) or physical process model. RT models are biome-independent because they are based on geometrical optical and radiative transfer theories by taking the interactions between LAI and influencing factors (e.g., the incident and observation angles, the canopy structure parameters and background effects) into consideration.

The third type is the hybrid model as a result of combining the empirical and physical approaches into a integrated LAI inverse model, which can inherit advantages of the simplicity of an empirical model as well as the biome-dependent characteristics of a process model [8, 19, 31]. Remote sensing derived LAI has been efficiently used as inputs to various ecological models [32-33]. However, Yao et al. [34] pointed out that for mixed grasslands of heterogeneity, LAI derived from remote sensing imagery with a large percentage of mixed pixels can hardly equal to *in-situ* data, resulting in inaccuracy and error. The higher the heterogeneity is, the lower the accuracy of LAI estimation will be. This is consistent with studies by He and Guo [35], suggesting that the remotely sensed LAI for heterogeneous area is also contributed by litter, soil and other canopy characteristics.

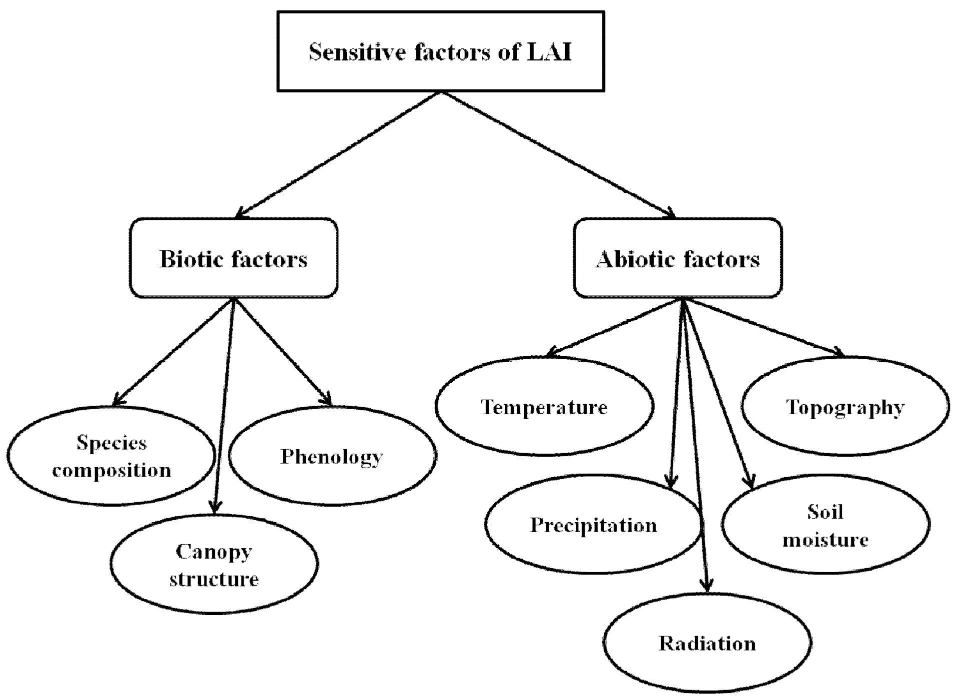
3. Spatiotemporal Variations of LAI and Sensitive Factors

LAI varies at different spatiotemporal scales, which is important to better understand the processes and patterns of ecosystems in different scales [36]. The spatial variation of global LAI changes with the distribution of vegetation biomes that shows high LAI values in tropical forest area, moderate LAI in agriculture and natural vegetation biomes, and low values in tundra and desert areas.

The seasonality is considered to be the most significant cause for the temporal variation of LAI in different vegetation biomes [37]. Li [9] concluded LAI of grasslands spatially varies within different land covers and temporally varies in different phenological phases including green up, maximum growth and senescence. Both the spatiotemporal variations of LAI are controlled by different sensitive factors in respects of biotic and abiotic categories. To improve the accuracy of LAI estimation, it is necessary to analyze the interrelation of these factors and their sensitivities to the spatiotemporal variation of LAI, and then parameters can be determined as inputs to the potential LAI model. Biotic factors consist of species composition, canopy structure, and phenology while and abiotic variables include temperature, precipitation, radiation, topography and soil moisture [38-40]. Canopy structure involves vegetation height, plant form percentage, and leaf angle distribution.

Slope, aspect, relative elevation, upslope length, and wetness index contribute to the topographical factor [16]. Soil moisture is a primary ecological parameter associated with LAI [41-43]. Consequently, LAI is considered as a function of the all the aforementioned factors [9]. Optical properties of the investigated vegetation, often quantified by vegetation indices (VIs) developed based on two or more spectral bands, are thought to be effective tools to measure the sensitivity of the aforementioned factors to LAI variation at different scales.

Figure1. Sensitive factors of LAI in mixed grasslands



Research has put efforts to investigate the relationships between LAI and its influential factors. Kramer et al. [43] concluded a linear relationship exists between LAI and the soil moisture and shows a direct proportion to the moisture deficit with some restrictions on threshold and time. He et al. [36] pointed out that the spatial variation of LAI at 30 m scales is determined by soil moisture and at 120 m controlled by topographical factor wetness index. Numerous studies show that VIs changes in the same trend with LAI or biomass below a maximum threshold called saturation value beyond which the VIs maintain unaffected by the variation of LAI [9, 44]. Some environmental factors merely control the LAI variation in either spatial or temporal scale, while others can contribute to the LAI variation at both scales at the same time. In view of the spatial aspect, topography is the primary determinant of large scale LAI, while soil moisture affects LAI at a smaller scale [36].

With regards to the temporal characteristic, climate variables considered as good indicators of LAI temporal variation, can reflect continuous vegetation conditions as well as leaf development in different times [41, 45-46]. The seasonal cycle of precipitation over land displays a strong relationship with the temporal variability of LAI due to the change of the hydrological cycle and the atmospheric circulation pattern [37]. Other variables, such as soil moisture controlled by topography, precipitation, soil texture and its chemical elements, can show the LAI variation at both spatiotemporal scales [37, 39]. However, there exists dependence to different extents between some of the LAI sensitive factors which repeatedly contribute to the spatiotemporal variation of LAI.For example, soil moisture is highly controlled by precipitation and topography [9, 39].

Therefore, it is necessary to identify the dependent influence among these sensitive factors for the accurate estimation of LAI at different spatiotemporal scales.

4. Remote Sensing Techniques for LAI Estimation

So far a collection of remote sensors have been explored to the application of modeling vegetation attributes, monitoring vegetation health and modeling biophysical processes [47-48]. For accurate LAI estimation taking account of spatiotemporal variation at different scales, satellite data with regard to spatial, temporal and spectral resolutions are supposed to be given to serious consideration and careful selection. Particularly in remote sensing modeling of LAI, satellite data of appropriate resolutions are required to be suitable for the spatiotemporal variation of LAI.

4.1 Available sensors

Different satellite sensors have different configurations in terms of orbital altitude, spatial resolution, spectral bands limits, and earth coverage period; especially radiometric properties acquired from different instruments are sensor-dependent [49-52]. Previous studies have shown that four satellite instruments are thought to be the most popular and frequently-used sensors in quantifying LAI. Those sensors involve the Advanced Very High Resolution Radiometer (AVHRR) carried on the meteorological satellite Television Infrared Observation Satellites (TIROS) and National Oceanic and Atmospheric Administration (NOAA) since 1978, Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's (National Aeronautics and Space Administration) Terra and Auqa satellites, Thematic Mapper/Enhanced Thermatic Mapper (TM/ETM+) aboard Landsat satellites, and High Resolution Visible Infrared (HRVIR) and Vegetation sensors aboard Satellite Pour l'Observation de la Terre (SPOT) 4 and 5 [8,30, 53-54] in Table 1.

Table1. Temporal, Spatial and spectral resolutions of available satellite data for LAI estimation

Satellite data	Temporal resolutions(day)	Spatial resolutions (m)	Spectral resolutions (number of bands)
AVHRR	1	1100	5 (Red, NIR,TIR, TIR, TIR)
MODIS	1	1000 500 250	29 (0.405μm - 14.385 μm) 5 (Blue, Green, NIR, MIR,MIR) 2 (Red, NIR)
SPOT Vegetation	1	1150	4 (Blue, Red, NIR, MIR)
TM	16	30 (band 1 through 5, 7) 120 (band 6)	7 (Blue, Green, Red, NIR, MIR,MIR, TIR,)
HRVIR SPOT	26	SPOT4: 20 (Green, Red, NIR, MIR); 10 (Pan) SPOT5: 20 (MIR); 10 (Green, Red, NIR, MIR); 2.5 (Pan)	5 (Green, Red, NIR, Pan, MIR)

I AVHRR

AVHRR was aimed to study the global climate and environmental change due to the high temporal resolution as well as the moderate spatial resolution (1.1 km ×1.1 km). There were 4 bands in the first AVHRR carried on TIROS satellite (1978) and AVHRR/2 was enhanced to 5 bands (0.6 um, 0.9 um, 3.5 um, 11 um and 12um respectively) initially aboard NOAA-7 (1981). Subsequently, an extra band (1.6um) was designed for the latest instrument version AVHRR/3 on NOAA-15(1998) [55].

Available 20-year records of global dataset make it possible to conduct continuously long-term monitoring of earth surface features such as land-covers, snow, ice and sea. Besides, changes in land-cover conditions over short periods can also be detected due to the cloud-free imagery obtained from high frequency coverage [48]. Operational NDVI products are generated from AVHRR data for monitoring vegetation conditions in different ecosystems. Canada-wide LAI maps were generated using 10-day cloud-free AVHRR imagery as well as SPOT Vegetation imagery since 1993 with validation by ground measurements and TM LAI scenes. Chen et al. [56] pointed out that the accuracy of AVHRR and SPOT Vegetation-derived LAI ranges from 50% to 70% with Landsat LAI as the standard due to the surface heterogeneity caused by mixed cover types.

Qi et al. [54] applied an approach by combining bidirectional reflectance distribution function (BRDF) model and traditional LAI-VI empirical relation in the AVHRR imagery and confirmed the possibility to estimate LAI in simple ways requiring less ground information of the target.

II MODIS

MODIS was aimed to provide long-term observation of global dynamics and processes of the land surface, oceanic as well as high atmospheric properties [38, 57]. It has more advantages in viewing any point of the earth surface in measurements of 36 spectral bands (0.405 to14.385 µm) at three spatial resolutions from 250 m/ pixel (bands 1 and 2), to 500 m/pixel (bands 3 through 7), and 1,000 m/pixel (bands 8 through 36). Three categories of MODIS products involving Surface Reflectance, Vegetation Indices (VIs) and Leaf Area Index-Fraction Photosynthetically Active Radiation (FPAR) at different spatiotemporal resolutions have great potential in estimating LAI. Ten types of global products in total are available for the Surface Reflectance category, twelve for the Vegetation indices and 4 for the Leaf Area Index-FPAR (Table 1). Yi et al. [30] compared two MODIS land surface reflectance data collections in wheat LAI retrieval and found the 8-day composite data are more preferable for LAI estimation due to the reduced cloud and aerosol impacts after composting.

Propastin and Erasmi [8] established a physical radiative transfer model to derive LAI at 250 m resolution using MOD13Q1 vegetation index products showing good compatibility with in situ measurements and the global MODIS 1000-m LAI product. However, Fang et al. [53] pointed out that MODIS standard LAI products based on a physical algorithm generally show both spatiotemporal discontinuity with higher LAI values, which is consistent with results by Fensholt et al. [33] that there is around 2-15% overestimation within MODIS LAI standard products due to a moderate offset unable to be explained by model or input uncertainties. Propastin and Erasmi [8] also argued that MODIS LAI product MOD15A2 underestimate LAI for moist rainforest biome characterized by higher LAI amplitude. Therefore, the potential of MODIS data in LAI estimation is in need of further exploration and experiments.

III Landsat TM/ETM+

TM (launched in Landsat 4, 5) is the predecessor of ETM+ (in Landsat 7) in Landsat series sensors with the cost of ETM+ data substantially reduced from TM. Table 1 shows the configuration of Landsat TM and ETM+ data with regard to spectral, spatiotemporal resolutions. Seven spectral bands are designed to distribute in the visible and infrared spectral regions. As high spatial resolution satellite data, both types of imagery are widely utilized to estimate LAI for different purposes [19, 58]. Various VIs, such as the Normalized Difference Vegetation Index (NDVI) and the Simple Ratio Index (SRI) derived from Landsat imagery, are related to ground-based LAI measurements in empirical models to retrieve large-area LAI [6, 8, 59-61].

Chen and Cihlar [6] estimated LAI of boreal conifer forests in Canada and found that TM data perform better in spring than in summer due to the minimized effect of understory and moss cover in spring. Brown et al. [1] reduced the background effects and improved the sensitivity of SR to the variation of LAI in boreal forests by modifying SR with the SWIR band information of TM imagery. Eklundh et al. [62] pointed out that there is a strong statistical relationship between LAI and reflectance in ETM+ band 7 and variation in LAI is sensitive to ETM+ visible wavelength than in NIR region particularly in band 3. Customarily LAI generated from Landsat imagery are used to validate other LAI products quantified by lower spatial-resolution imagery such as MODIS or SPOT Vegetation [53].

IV SPOT HRVIR and Vegetation

SOPT 4 and SOPT 5 are respectively the fourth (1998) and fifth (2002) generation of the entire SPOT satellite series, carrying both HRVIR and Vegetation sensors for which different spatial, temporal and spectral resolutions are respectively shown in Table 1 [63].

Particularly the SWIR band (1580-1750nm) sensitive to surface moisture can improve the accuracy of LAI estimation [1, 64]. Numerous studies have focused on investigating LAI based on SPOT HRVIR and Vegetation data. Soudani et al. [52] compared the potential use of IKONOS, ETM+ and SPOT HRVIR sensors to estimate LAI in forest and concluded that the three sensors are similar in bare soil or sparse vegetation while ETM+ and HRVIR are more accurate that IKONOS in dense vegetation areas. However, Kraus at el. [65] assessed the LAI in East African rainforest ecosystems by comparing HRVIR, ASTER and MODIS data draw an inverse conclusion that ASTER data performed better than others in LAI derivation. He et al. [36] showed that NDVI calculated from SPOT4 HRVIR satellite data has a significant correlation to wetness index and LAI which helps identify the impact of topography on spatial variation of grassland LAI in Saskatchewan, Canada.

4.2 Appropriate temporal, spatial and spectral resolutions

Various remote sensing data with different spatial, temporal and spectral resolutions present a promising opportunity to capture the spatiotemporal variation in LAI. How to identify appropriate remote sensing data is the key issue for grassland LAI estimation in a dynamic way.

Three spatial scales (20 m, 40 m and 120 m) are significant for LAI variation in semi-arid mixed grassland. Scales at 20 m and 40 m are accounted for the variation of soil moisture while 120 m is controlled by topographical variation [36]. So far, spatial scale larger than 120 m has not been identified for LAI which might be determined by the variation of other sensitive factors. Spatial scale investigation of different LAI-sensitive factors aid in the selection of suitable imagery from diverse satellite data of multiple spatial resolutions (e.g., 250 m, 500 m and 1000 m for MODIS, 30 m for Landsat TM/ETM+, 20 m for SPOT 4 HRVIR, 10 m for SPOT 5 HRVIR, 1150 m for SPOT Vegetation, and 1000 m for AVHRR).

Meanwhile, all the aforementioned satellite data can also make it possible to explore the variation of different sensitive factors and LAI at different spatial scales. Wu et al. [66] and He et al. [16] suggest that the detection of LAI spatial sensitivity depends on the spatial resolution of remote sensing imagery which agrees with a previous study by [67]. Especially for the semi-arid grasslands characterized by high heterogeneity of mixed cover types, determining an appropriate spatial scale can help improve the accuracy of ecological studies by using upscaling (processing images from small pixel size to large pixel size) or downscaling (processing images from large pixel size to small pixel size) approaches [68]. However, it is difficult to accurately extract the spatial information of LAI by merely processing image pixels of mixed cover types [16, 53]. To solve this problem, Chen et al. [56] emphasized that the accurate information of image subpixel mixture contributed by different cover types is considered as the key to raise the accuracy of such LAI retrieval.

Concerning the temporal aspect, satellite imagery of multiple revisiting frequencies (e.g., 1 day for MODIS, 16 day for Landsat TM/ETM+, 26 day for SPOT HRVIR, 1 day for SPOT Vegetation, and 1 day for AVHRR) makes it possible to quantify temporal variation of LAI in the entire growing season (the green-up, the maximum growing, and the senescence) due to timely and effective repeated observations [69]. However, numerous studies have demonstrated that remote sensing images suffer from cloud contamination (Clouds and Cloud shadows in the imagery) which results in temporal poor coverage of land surface; sometimes only a few images can be obtained during the whole vegetation growing season [70-71]. Two potential ways can solve this problem. Jensen [48] suggests that imagery of high frequency of coverage (e.g. AVHRR) can increase the possibility to obtain cloud-free observations and to detect land-cover conditions over short periods. Also Houborg et al. [72] stated that remote sensors such as MODIS can provide continuous daily data, which holds the potential to conduct LAI analysis in different time series. Another method to fill the gap caused by the cloud effect is to improve the detection and removal of clouds and their shadows from various satellite images [47].

For example, Choi and Bindschadler [73] pointed out that the Automatic Cloud Cover Assessment (ACCA) can indentify clouds in Landsat imagery due to their high albedo in the visible spectrum and cold temperature in the infrared spectrum. Wang et al. [74] applied such a scheme to TM imagery and generated the cloud-free composite image by using image fusion technique and integrating complementary information. Also, Tseng et al. [75] implemented the same method to multitemporal SPOT images and derive cloud-free mosaic images. However, Li [9] argued that daily LAI estimation can be realized by an interpolation or extrapolation of LAI obtained on neighboring dates due to the relatively stable condition of vegetation in grasslands over a short time period.

The spectral resolution of remote sensing data mainly determines the development of diverse VIs which are sensitive to various influential factors of LAI (e.g., canopy structure, soil moisture, and phenology).

VIs are defined as a dimensionless and radiometric value estimated from of multispectral information of remote sensing imagery to measure green vegetation abundance and activity (e.g., LAI, percentage green cover, chlorophyll concentration, and green biomass) (Jensen, 2007). VIs allows for monitoring or quantifying LAI variation because of a close positive relationship with LAI below the saturation threshold (Li and Guo, 2010). Hundreds of VIs were developed based on combined information of different spectral bands, and a majority makes use of the inverse relationship between red and near-infrared reflectance associated with green vegetation (Haboundane et al., 2004; Delalieux et al., 2008).

Li and Guo (2010) pointed out that VIs developed based on reflectance ranging from 550 nm to 750 nm are not only sensitive to LAI but also responsive to chlorophyll leading to inaccuracy of LAI estimation.

Therefore, Modified Chlorophyll Absorption Ratio Indices (MCARI) was developed utilizing green, red and near infrared bands to reduce the chlorophyll sensitivity but to increase that of LAI variation (Daughtry et al., 2000; Haboundane et al., 2004). The shortwave infrared (SWIR) region sensitive to moisture content is another option to distinguish vegetation from soil background due to the different water contents in vegetation and soil. Brown et al. (2000) modified the SRI by utilizing SWIR information to develop a new VI called Reduced Simple Ratio (RSR) which demonstrated increased sensitivity of LAI and minimized background influence in the boreal forests of Canada. Li and Guo (2010) investigated the performances of 16 VIs on temporal estimation of LAI in mixed grasslands and found NDVI is the most appropriate one for LAI variation during the entire growing season.

In addition, it is necessary to reduce the impact of atmospheric effects on VIs for improved LAI estimation by taking advantage of blue band information which is sensitive to atmospheric scattering and absorption. Atmospherically Resistant Vegetation Index (ARVI) and Soil and Atmospherically Resistant Vegetation Index (SARVI) were developed with this purpose (Kaufuman and Tanre, 1992; Huete and Liu 1994). Besides, for semiarid mixed grasslands, abundant of dead materials can significantly impact the LAI variation, which leads to a new VI named the litter-corrected adjusted transformed soil-adjusted vegetation index (L-ATSAVI) proposed by He et al. (2006a) by incorporating a litter adjustment factor (L) to reduce effects of both soil background and litter on the LAI estimation by about 10%. All of the available satellite imagery have red and near infrared spectral bands which can aid in deriving NDVI as well as SWIR bands for reducing background effects. TM, SPOT Vegetation and MODIS have blue bands information for correcting atmospheric noise. However, litter adjusts factor utilizing the band 2000, 2100 and 2200 (not available in the aforementioned satellite imagery) can only be derived in hyperspectral reflectance (Table 2-6).

4.3 Remote sensing models for LAI estimation

Numerous studies have been conducted to develop different types of remote sensing models for LAI estimation at different spatiotemporal scales. Currently, there are primarily three approaches involving empirical models, physical models and hybrid models for LAI estimation [30, 54, 58].

Empirical models are based on an empirical relation between in situ LAI measurements and remotely sensed VIs [54]. This approach can be easily implemented to retrieve LAI from local to regional areas, and have been effectively used in different studies [56, 76-77]. However, the first limitation of empirical models is the saturation problem (low sensitivity of VIs to LAI of high values). In addition, LAI derived from such models are site-season specific and scale-dependent, which means there is no single LAI-VI equation with fixed coefficients available for satellite imagery of different surface types [54]. Moreover, it is difficult to determine a suitable VI of less sensitivity to non-vegetation related factors (e.g., soil background, atmospheric conditions, topography and bidirectional nature of surfaces) [78-80]. NDVI is the most widely used VI for LAI estimation, which has been demonstrated in studies by [6, 34, 61]. However, Propastin and Erasmi[8] concluded that saturation and scale problems in the application of NDVI are still unsolved. Furthermore, for mixed grasslands of heterogeneity, the NDVI-LAI empirical models cannot eliminate the reflectance contributed by dead material and bare soil, which necessitate the development of other VIs to improve the estimation.

Physical models are developed by the inversion of a radiative transfer (RT) equation, as a function of canopy, leaf and soil background characteristics based on theoretical laws [81-82]. Compared with the empirical models, RT models are able to physically describe the transfer and interaction of radiation, and thus can be applied widely in different vegetation surfaces [72]. However, the disadvantages within RT models are time-consuming computation and difficultly-obtained input parameters [54].

In order to improve the computation speed, two commonly used methods, the Lookup table (LUT) and the neural network (NN), are explored by many studies to optimize the procedure [83-86]. Another limitation of RT models is caused by the cloud cover and lack of regional data for validation [8] Therefore, RT models need to be incorporated with ground-based information on canopy transmission of vegetation [87].

The hybrid approach combines physical basis and LAI-VI empirical relationship into one integrated model, which is aimed to overcome the limitations of both LAI-VI and physical models [54]. A bidirectional reflectance distribution function (BRDF) model is inverted to generate a training dataset (LAI and pixel values) which was then used to establish a LAI-VI equation for large-scale LAI estimation based on remote sensing. The advantage of this approach is that little information of study target as well as few *in-situ* measurements is required. However, it is a preference to use *in-situ* LAI instead of the physical model-inversed LAI for the LAI-VI equation validation if LAI measurements are available.

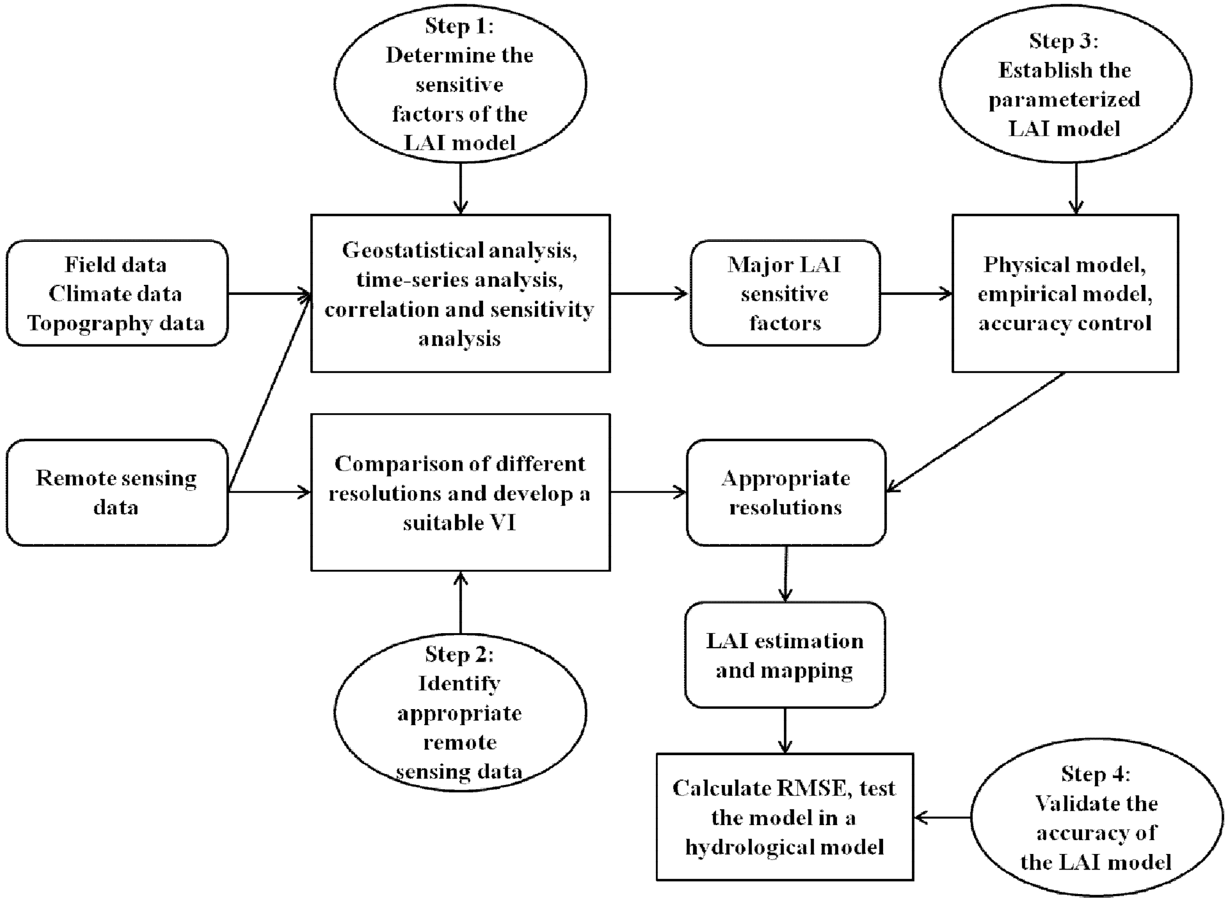
5. Challenges of Remote Sensing Of LAI

Although a lot of studies have been done on LAI estimation using remote sensing technique, the accuracy is relatively low and lacks of a dynamic characterization. In particular, a majority of studies focused on to the relationship between VIs and LAI with only a smaller fraction of research carried out for LAI spatiotemporal sensitivity analysis. Since the influence of sensitive factors exists in LAI scale studies, then how to incorporate the major influential factors of LAI spatiotemporal variation is of great significance in mixed grasslands. In addition, the appropriate temporal, spatial, and spectral resolutions of remote sensing data for LAI estimation are still poorly identified. Therefore, the spatiotemporal scale problem of LAI estimation has not yet been solved completely. Satellite imagery of discontinuously-temporal and spatially-mixed pixels for heterogeneous grasslands always results in the inaccuracy of LAI variation. To determine the optimal temporal, spatial and spectral resolutions of suitable satellite data for grassland LAI derivation is in need of further exploration. Moreover, the current LAI estimation models, whether empirical or physical ones, have their own limitations. Therefore, to develop a parameterized model combining advantages of both empirical models and physical models has great potential in improving the accuracy of LAI estimation at different spatiotemporal scales for mixed grasslands.

6. A Spatiotemporally Parameterized Model for Mixed Grasslands

Our research hypothesis is that a spatiotemporal parameterized LAI model can be established based on remote sensing to improve the accuracy of LAI estimation in a dynamic way for mixed grasslands. The overall purpose of this parameterized model is to improve the accuracy of LAI estimation in a mixed grassland ecosystem. Four steps are as follows, 1) Determine sensitive factors of LAI spatiotemporal variation in mixed grasslands with the aim of preparing input variables for the target LAI model. 2) Identify satellite data of appropriate temporal, spatial and spectral resolutions for the LAI estimation at different spatiotemporal scales in mixed grasslands.3) Establish a parameterized LAI model that can provide spatiotemporal variation of vegetation canopy in mixed grasslands. 4) Validate the accuracy of the LAI model and test it in t hydrological model CRHM.

Figure 2. A synthesized framework of establishing a spatiotemporally parameterized LAI model



6.1 Determine the sensitive factors for the LAI model

For the establishment of a spatiotemporal LAI estimation model, it is important to firstly investigate what sensitive factors can influence the spatiotemporal variation of LAI, and to determine which factors can be used as the input variables for the LAI model. This step is necessary to provide a theoretical base for accurately modeling LAI in the mixed grasslands. Previous studies have revealed that possible sensitive factors of LAI spatiotemporal variation are species composition, canopy structure, penology, topography, soil moisture, precipitation, temperature, radiation and VIs. To accomplish step 1, spatiotemporal variation analysis will be conducted in the aforementioned possible factors as well as in situ LAI, and correlation as well as sensitive analysis [36, 88] between those factors and LAI will also be investigated together to determine the final input variables for the spatiotemporal parameterized LAI estimation model. Both Field and satellite data are required to verify the effects of those factors on the spatiotemporal scale variation of LAI.

6.1.1 Identify the spatiotemporal variation of the sensitive factors and LAI

Considering different types of variation scales, the available sensitive factors of LAI in my study area can be classified into spatial-sensitive (topography), temporal-sensitive (precipitation and temperature) and spatial-temporal-sensitive factors (soil moisture).

Geostatistical analysis plays an important role to investigate the spatial variation in ecosystem studies. Particularly semivariogram and wavelet are two commonly-use approaches to verify the spatial scales of different quantities. In this study wavelet method will be selected to identify the spatial scales of LAI and its spatial-sensitive as well as spatial-temporal-sensitive factors due to the information of variation transition it can provide which the other method fails to [16]. Among the four familiar wavelet families (Haar, Daubechies Least Asymmetric, Mexican Hat and Morlet), the Morlet mother function is thought to be the most suitable one for scale investigation due to the balance of time and frequency location [89].

Therefore, the continuous Morlet wavelet transformation will be explored to find the periodicity of the repeated spatial pattern known as "scale of variation" of *in-situ* spatial-sensitive factors (e.g., soil moisture, topography) as well as LAI along transects by calculating the wavelet transform over a continuous range of dilation scales in MATLAB platform [16, 90].

It is impossible to measure the in situ LAI frequently due to the difficulty of obtaining multiple entry permits to the study area, the insufficient labor and unavailable transportation tools for frequent long-distance travelling. Vegetation index such as NDVI has been proved to be a good indicator of LAI in broad studies of deciduous forest, grasslands and croplands [60, 9-93]. Thus, for the temporal analysis of LAI, it is necessary to investigate the time-series characteristics of vegetation-represented VI such as NDVI derived from satellite data of high temporal resolution (e.g. MODIS, AVHRR) to determine the temporal scales of LAI in the mixed grasslands. Other temporal-sensitive and spatial-temporal-sensitive factors (e.g. temperature and precipitation) should also be conducted time-series analysis to determine the feasible temporal scales of LAI.

6.1.2 Determine the major sensitive variables the LAI model

First, the statistical correlation and sensitivity between possible variables and LAI will be analyzed to maintain the most insensitive factors, which are considered as a perquisite step for the next determination concerning the sensitivity to spatiotemporal scales. The dependence between factors should also be investigated in this step to select model variables as independent as possible. Then by comparing the spatiotemporal scales between the available sensitive factors and LAI, the factors with similar spatiotemporal patterns of LAI variation will be considered as the input variables to the parameterized LAI model.

Different combinations of temporal-sensitive and spatial sensitive factors yield a parameterized LAI model with a group of sub-functions under different conditions of various spatiotemporal scales. That means the target parameterized LAI model is not an individual function, but consists of a set of equations of distinctive parameters or coefficients within a generic function (Equation 1.).

$$LAI_{i-1} = f(TOP, SM, VI_i, T_{i-1}, P_{i-1}) \qquad (1)$$

Where i is time, VI is the vegetation index, TOP is topography factor, SM is soil moisture, T is temperature, and P is precipitation. The time unit can be bi-weekly, monthly or growing phases. For example, assuming the LAI model is developed based on a linear relationship between the dependent variables (LAI) and independent variables (sensitive factors) (Equation 2.), if the spatial-sensitive factor of LAI at 20 m is soil moisture while temperature is the temporal-sensitive factor from vegetation greenup to maximum growth.

Then the first sub-function can give more accurate estimation of LAI under this spatiotemporal scale condition (spatial scale of 20 m and temporal scale from greenup to maximum growth). If topography is the controller of LAI spatial variation at 120 m while precipitation and VI are the most sensitive temporal factors from maximum growth to senescence, then the second sub-function can be the most suitable equation to quantify LAI under this condition (spatial scale of 120 m and temporal scale from maximum growth to senescence.

$$LAI_{i-1} = aTOP + bSM + cVI_i + dT_{i-1} + eP_{i-1} + f \qquad (2)$$

$$= \begin{cases} a = 0, c = 0, e = 0, f = 0 \text{ (20m, from greenup to maximum growth)} \\ b = 0, d = 0, f = 0 \text{ (120m, from maximum growth to senecence)} \\ \vdots \end{cases}$$

6.2 Identify appropriate satellite data for LAI estimation

To achieve this objective, the temporal resolution of possible satellite data should at least cover the three phonological phases (Greenup, Peak growth, and Senescence) or even provide higher temporal coverage of the mixed grasslands in our study areas. Daily continuously remote sensing imagery AVHRR, MODIS and SPOT Vegetation will be used to derive VI to investigate the sequential variation of LAI in a higher frequency by conducting chronological time-series analysis. Satellite data such as TM (16 days) and SPOT (26 days) will also be utilized to study the temporal variation of LAI at a coarse scale such as bi-week periods or monthly phonological phases.

The optimal satellite data of appropriate spatial resolution should be able to detect the spatial scales of LAI variation as well as its sensitive factors in mixed grasslands.

According to the spatial scales of different variables identified in step 1, the remote sensing imagery of corresponding spatial resolutions will be chosen as the spatially promising data for the establishment of an accurate LAI model.

The concerning of data spectral resolution mainly focuses on the derivation of different VIs which require distinctive combination of spectral bands. All available satellite data have the vegetation most-sensitive bands Red and NIR. To reduce the background, atmospheric and chlorophyll influences, a more accurate VIs providing specific information associated with vegetation canopy necessitate the utilization of other spectral bands besides the Red and NIR, such as MIR (characterized bands in 0.9 nm, 1.1nm, 1.4nm and 1.9nm of moisture content) for vegetation detection, or Green band helpful for reduce chlorophyll effect. Therefore, multiple VIs (e.g. NDVI, RSR, and SARVI) will be attempted to generate by making full use of the available satellite imagery. The best input VI variable for the LAI model will be determined by ways of careful quantitative comparison.

Since the temporal, spatial and spectral configuration of each certain remote sensor is fixed, then the most comparatively appropriate imagery will be finally selected to quantify VI for better estimation of LAI in mixed grasslands. If the temporal resolution fails to estimate the temporal variation of LAI but the spatial resolution is acceptable, then a data filtering algorithm of reducing clouds effect will be applied to generate continuous images at this spatial scale. Otherwise, if the spatial resolution is too low to reflect the spatial variation of LAI but the temporal resolution is satisfied, then remote sensing downscaling technique will be explored to extract the sub-pixel information to improve the spatial quality of imagery. Or if the spatial resolution is too high for LAI scale studies, then remote sensing upscaling technique will be considered for the adjustment of imagery spatial resolution. However, those remote sensing techniques (filtering, upscaling and downscaling) is complex and requires huge amount of labor and time. It is expected to avoid such procedures by directly using the original satellite data at a relatively acceptable level.

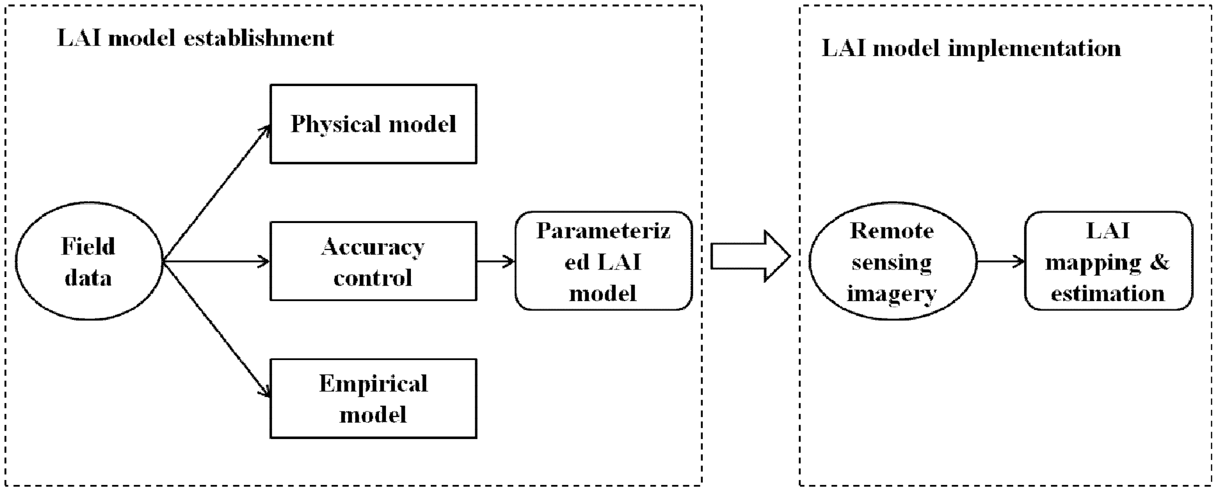
6.3 Establish the parameterized LAI model

To take the advantages of the easy computation of empirical models and physical aspects of radiative transfer models, a parameterized model incorporating the two aforementioned approaches will be proposed in this study to improve the accuracy of LAI estimation in the semi-arid grassland. The process to establish this LAI model is based on model inversion theory. A graphic presentation of the proposed model consisting of model establishment and implementation is illustrated in Figure 6. Three sequential steps involving, physical equation building, empirical equation building and accuracy control are designed for the section of model establishment. Firstly a physical LAI model will be developed based on a bidirectional reflectance distribution function (BRDF) physical theory (Equation 3.), and then an empirical equation by relating LAI and its spatiotemporal sensitive factors with a set of unknown parameters or coefficients in a linear or other fitting forms will also be established for different spatiotemporal scales (Equation 1.).

The physical model can be fixed through an iterative inversion process using field measured data including soil reflectance, leaf structure parameter, canopy optical characteristics, leaf-scattering coefficients and in situ LAI under certain illumination and observation conditions [9, 54]. However, boundary conditions of different variables should be detected to avoid process failure. The empirical equation is the target parameterized model for LAI estimation using remote sensing data, because it can detect LAI variation at different scales by introducing different temporal and spatial sensitive factors. Also, empirical equations can be more conveniently applied into satellite imagery by utilizing different types of VIs.

Due to the accuracy of physical deviation taking various environmental conditions into consideration; the physical modeled LAI will be used to control the accuracy (Equation 4.) as a reference standard to fix the parameters or coefficients for the empirical model under different scale conditions. A best-fit parameterized equation will be determined by performing an iterative optimization until the accuracy criteria δ^2 can be satisfied with a given threshold. The difference between the proposed model and the model by Qi et al. [54] is that the former can provide spatiotemporal variation of LAI by incorporating different scale sensitive factors. Finally, this parameterized empirical model will be applied into satellite imagery to derive LAI estimation as well as LAI mapping at different spatiotemporal scales.

Figure 6. Flowchart of the parameterized LAI modeling



$$LAI_p = f(\rho_s, r, LAD, \rho_{\lambda L}, \tau_{\lambda L}) \quad (3)$$

Where LAI_p stands for estimated LAI using the physical equation, r is reflectance or radiance, LAD is leaf angle distribution describing canopy structure; $\rho_{\lambda L}, \tau_{\lambda L}$ are canopy leaf optical properties (single leaf reflectance and transmittance); ρ_s is the soil reflectance.

$$\delta^2 = \sum_{i=1}^{N}(LAI_p - LAI_{i-1})^2 \quad (4)$$

Where δ^2 is a statistical merit function as an accuracy criteria here and N is the calculation time, by examining the corresponding δ^2 values, the best-fit parameterized empirical equation for spatiotemporal LAI estimation can be obtained [54].

6.4 Validate the accuracy of the LAI model

For the final step the parameterized LAI model should be validated using accuracy assessment methods to measure the discrepancy between the modeled LAI and the ground LAI in mixed grassland areas. The accuracy of LAI derived from the proposed parameterized model should be analyzed quantitatively. For example, to test the LAI model in the CRHM model provides macro function to develop different models, so the parameterized LAI model can be incorporated into CRHM by writing a specific LAI module to replace the original constant LAI by LAI of spatiotemporal variation information. One input of the CRHM model such as evaportranspiration will be selected to test the sensitivity of the CRHM model to the parameterized LAI. Comparison will be made between the original constant LAI and the modeled LAI in the performance of evaportranspiration process.

7. Expected Results and Contributions

This research will fill the gaps in mixed grassland LAI estimation. First, with more sensitive factors of LAI spatiotemporal variation revealed, LAI scale estimation will have stronger theoretical basis. Besides, remote sensing data of appropriate spatial, temporal and spectral resolutions will be explored to provide more potential for LAI study at different scales. Last but not least, a new parameterized LAI estimation model taking advantages of both empirical and physical approaches can improve the accuracy of LAI estimation in mixed grasslands at different spatiotemporal scales. With this improved LAI estimation as an important input, the performance of climatologic, hydrological and other land-surface process models will also be enhanced. This will significantly contributed to the whole ecosystem sand global climate change study.

Acknowledgments

This research was supported by NSERC and ISTP Canada. The authors are grateful to the anonymous reviewers whose suggestions have been helpful in preparation of the manuscript. The authors also would like to acknowledge Carmen Finnegan who helped to improve the English language of this manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

References and Notes

Brown, L.; Chen J.M.; Leblanc, S.G.; Cihlar, J. A shortwave Infrared Modification to the Simple Ratio for LAI Retrieval in Boreal Forests: An Image & Model Analysis. *Remote Sensing of Environment* **2000**, *7*, 16-25.

Chen, J.M.; Black, T.A. Defining leaf area index for non-flat leaves. *Plant, Cell and Environment* **1992**, *15*, 421-429.

Johnson, I. R.; Thornley, J. H. M. Vegetative crop growth model incorporating leaf area expansion and senescence, and applied to grass. *Plant, Cell and Environment***1983**, *6*, 721-729.

Nemani, R.; Pierce, L.; Running, S,; Band, L. Forest ecosystem processes at the watershed scale: sensitivity to remotely-sensed Leaf Area Index estimates. *International Journal of Remote Sensing***1993**, *14*, 2519-2534.

Curran, P.J.; Steven, M.D. Multispectral remote sensing for the estimation of green leaf area index. Philosophical Transactions of the Royal Society of London. *Series A, Mathematical and Physical Sciences* **1983**, *309*, 257-270.

Chen, J.M.; Cihlar, J. Retrieving LAI of boreal conifer forests using Landsat TM images. *Remote Sensing of Environment* **1996**, *55*, 153-162.

Chen, J. M.; Liu, J.; Cihlar, J.; ;Guolden, M. L. Daily canopy photosynthesis model through temporal and spatial scaling for remote sensing applications. *Ecological Modelling* **1999**,*124*, 99-119.

Propastin, P.; Erasmi, S. A physically based approach to model LAI from MODIS 250m data in a tropical region. *International Journal of Applied Earth Observation and Geoinformation***2010**, *12*, 47-59.

Li, Z. *Improved leaf area index estimation by considering both temporal and spatial variations*. MSc Thesis. University of Saskatchewan, Canada, 2008.

Turner, M.G. Landscape ecology: the effect of pattern on process. *Annual Review of Environment and* Resources**1989**, *20*, 171-197.

Shen, L.; He, Y.; Guo, X. Exploration of *Loggerhead Shrike* Habitats in Grassland National Park of Canada Based on *in Situ* Measurements and Satellite-Derived Adjusted Transformed Soil-Adjusted Vegetation Index (ATSAVI). *Remote Sens.* **2013**, *5*, 432-453.

He, Y.; Guo, X,; Wilmshurst, J. Studying mixed grassland ecosystems I: suitable hyperspectral vegetation indices. *Canadian Journal of Remote Sensing* **2006**,*32*, 98-107.

Lobo, A.; Moloney, K.; Chic, O.; Chiariello, N. Analysis of finescale spatial pattern of grassland from remotely sensed imagery and field collected data. *Landscape Ecology***1998**, *13*, 111-131.

Fan, L.; Gao, Y.; Brück, H.; Bernhofer, Ch. Investigating the relationship between NDVI & LAI in semiarid grassland in Inner Mongolia using *in-situ* measurements. *Theoretical & Applied Climatology***2007**, *95*, 151-156.

Guo, X.; Wilmshurst, J.; McCanny, S.; Fargey, P; Richard, P. Measuring Spatial and Vertical Heterogeneity of Grasslands Using Remote Sensing Techniques. *Journal of Environmental Informatics***2004**, *3*, 24-32.

He, Y.; Guo, X.; Wilmshurst, J. Studying mixed grassland ecosystems II: optimum pixel size. *Canadian Journal of Remote Sensing***2006**, *32*, 108-115.

Zhang, C.; Guo, X. Measuring biological heterogeneity in the northern mixed grassland: A remote sensing approach. *The Canadian Geographer***2007**, *51*,462-474.

Pomeroy, J.W.; Gray, D.M.; Brown, T.; Hedstrom, N.R.; Quinton, W.L.; Granger, R.J.; Carey, S.K. The cold regions hydrological model: a platform for basing process representation and model structure on physical evidence. *Hydrological processes***2007**, *21*, 2650-2667.

Zheng, G.; Moskal, L.M. Retrieving Leaf Area Index (LAI) Using Remote Sensing: Theories, Methods and Sensors. *Sensors* **2009**, *9*, 2719-2745.

Jonckheere, I.; Fleck, S.; Nackaerts, K.; Muys, B.; Coppin, P.; Weiss, M.; Baret, F. Review of methods for in situ leaf area index determination - Part I. Theories, sensors and hemispherical photography. *Agriculture for Meteorology***2004**, *121*, 19-35.

Gobron, N.; Pinty, B.; Verstraete, M.M. Theoretical limits to the estimation of the leaf area index on the basis of visible and near-infrared remote sensing data. *IEEE Transactions on Geoscience and Remote Sensing***1997**, *35*, 1438-1445.

Chason, J.W.; Baldocchi, D.D.; Huston, M.A. A comparison of direct and indirect methods for estimating forest canopy leaf area. *Agricultural and Forest Meteorology* **1991**, *57*, 107-28.

Shen, L.; He, Y.; Guo, X. Suitability of the normalized difference vegetation index and the adjusted transformed soil-adjusted vegetation index for spatially characterizing Loggerhead Shrike habitats in North American mixed prairie. *Journal of Applied Remote Sensing***2013**. *7(073574)*, 1-17. doi: 10.1117/1.JRS.7.073574

He, Y.; Guo, X.; Wilmshurst, J. Comparison of different methods for measuring LAI in a mixed grassland. *Canadian Journal of Plant Science* **2007**, 87, 803-813.

Chen, J.M.; Rich, P.M.; Gower, T.S.; Norman, J.M.; Plummer, S. Leaf area index of boreal forests: theory, techniques and measurements. *Journal of Geophysical Research* **1997**, 102, 29429- 29444.

Kucharik, C.J.; Norman, J.M.; Murdock, L.M.; Gower, S.T. Characterizing canopy nonrandomness with a multiband vegetation imager (MVI). *Journal of Geophysical Research* **1997**, *102*, 29455-29473.

Hunt, T. E.; Haile, F. J.; Hoback, W. W.; Higley, L. G. Indirect measurement of insect defoliation. *Environmental Entomolgy***1999**, *28*, 1136-1139.

Weiss, M.; Baret, F.; Smith, G. J.; Jonckheere, I.; Coppin, P. Review of methods for in situ leaf area index (LAI) determination. Part II. Estimation of LAI, errors & sampling. *Agriculture of forest meteorology* **2004**. 121, 37-53.

Sprintsin, M.; Karnieli, A.; Berliner, P.; Rotenberg, E.; Yakir, D.; Cohen, S. The effect of spatial resolution on the accuracy of leaf area index estimation for a forest planted in the desert transition zone. *Remote Sensing of Environment***2007**, *109*, 416-428.

Yi, Y.; Yang, D.; Huang, J.; Chen, D. Evaluation of MODIS surface reflectance products for wheat leaf area index (LAI) retrieval. *Journal of Photogrammetric & Remote Sensing* **2008**, 63, 661-677.

Fernandes, R.; Leblanc, S.J. Parametric (modified least squares) and non-parametric (Theil–Sen) linear regressions for predicting biophysical parameters in the presence of measurement errors. *Remote Sensing of Environment***2005**, *95*, 303-316.

Kotchenova, S. Y.; Song, X.; Shabanov, N. V.; Potter, C. S.; Knyazikhin, Y.; Muneni, R. B. Lidar remote sensing for modeling gross primary production of deciduous forests. *Remote Sensing of Environment***2004**, *92*,158-172.

Fensholt, R.; Sandholt, I.; Rasmussen, M. S.; Stisen, S.; Diouf, A. Evaluation of satellite based primary production modeling in the semi-arid Sahel. *Remote Sensing Environment* **2007**. *105*,173-188.

Yao, Y.; Liu, Q.; Liu, Q.; Li, X. LAI Inversion Uncertainties in Heterogeneous Surface. *Journal of remote sensing***2007**, 4, 299-311.

He, Y.; Guo, X. Leaf area index estimation using remotely sensed data in a mixed grassland ecosystem. *Prairie Perspectives***2006**, 9, 105-117.

He, Y.; Guo, X.; Si, B.C. Detecting grassland spatial variation by a wavelet approach. *International Journal of Remote Sensing 2007*, *28*, 1527-1545.

Bart, J. J. M.; van den, H.; Pedro, V.; Sietse, O. L. Impact of leaf area index seasonality on the annual land surface evaporation in a global circulation model. *Journal of Geophysical Research* **2003**, *108*, 4191-4203.

Loik, M.E.; Breshears, D.D.; Lauenroth, W.K.; Belnap, J. A multi-scale perspective of water pulses in dryland ecosystems: climatology and ecohydrolog of the western USA. *Oecologica***2004**, *141*, 269-281.

Western, A.W.; Blöschl, G.; Grayson, R.B. Geostatistical characterization of soil moisture patterns in the Tarrawarra catchment. *Journal of Hydrology***1998**, 205, 20-37.

Zhang, X.; Friedl, M.A.; Schaaf, C.B.; Strahler, A.H. Climate controls on vegetation phenological patterns in northern mid- & high latitudes inferred from MODIS data. *Global Change Biology* **2004**, *10*, 1133-1145.

Loustau, D.; Berbigier, P.; Granier, A.; El Hadj Moussa, F. Interception loss,through fall and stemflow in a maritime pine stand. I. Variability of throughfall and stemflow beneath the pine canopy. *Journal of Hydrology***1992**, 138, 449-467.

Loustau, D.; Berbigier, P.; Roumagnac, P.; Arruda-Pacheco, C.; David, S.A.; Ferreira, M.I.; Perreira, J.S.; Tavares, R. Transpiration of a 64-year-old maritime pine stand in Portugal. I. Seasonal course of water flux through maritime pine. *Oecologia***1996**, *107*, 33-42.

Kramer, K.; Leinonen, I.; Loustau, D. The importance of phenology for the evaluation of impact of climate change on growth of boreal, temperate and Mediterranean forests ecosystems: an overview. *International Journal of Biometeorology***2000**, 44, 67-75.

Carlson, T.N.; Riziley, D. A. On the Relation between NDVI, Fractional Vegetation Cover, and Leaf Area Index. *RemoteSensing of Environment***1997**, *62*, 241-252.

Svetlana, L.; Göran, Å. Temperature sensitivity of nitrogen productivity for Scots pine and Norway spruce. *Trees* **2004**, *18*, 312-319.

Elliott, J. A.; Jones, I.D., Thackeray, S.J. Testing the sensitivity of phytoplankton communities to changes in water temperature and nutrient load, in a temperate lake. *Hydrobiologia***2006**, *559*, 401-411.

Wang, K.; Franklin, S.E.; Guo, X.; He, Y.H.; McDermid, G.J. Problems in remote sensing of landscapes and habitats. *Progress in physical geography***2009**, *33*,747-768.

Jensen, J.R. *Remote sensing of the environment: an Earth resource perspective,* 2nd ed.; Pearson Prentice Hall: Upper Saddle River. NJ, USA, 2007.

Hill, J.; Aifadopoulou, D. Comparative analysis of Landsat-5 TM and SPOT HRV-1 data for use in multiple sensor approaches. *Remote Sensing of Environment***1990**, *34*, 55-70.

Teillet, P. M.; Staenz, K.; Williams, D. J. Effects of spectral spatial and radiometric characteristics of remote sensing vegetation indices of forested regions. *Remote Sensing of Environment***1997**, *61*, 139-149.

Steven, M. D.; Malthus, T. J.; Baret, F.; Xu, H.; Chopping, M. J. Intercalibration of vegetation indices from different sensor systems. *Remote Sensing of Environment***2003**, *88*, 412–422.

Soudani, K.; François, C.; Maire, G.L.; Dantec, V.L.; Dufrêne, E. Comparative analysis of IKONOS, SPOT, and ETM+ data for leaf area index estimation in temperate coniferous and deciduous forest stands. *Remote Sensing of Environment***2006**, *102*, 161-175.

Fang, H.; Liang, S.; Townshend, J.R.; Dickinson, R.E. Spatially & temporally continuous LAI data sets based on an integrated filtering method: Examples from North America. *Remote sensing of Environment* **2008**, *112*, 75-93.

Qi, J.; Kerr, Y.H.; Moran, M.S.; Weltz, M.; Huete, A.R.; Sorooshian, S.; Bryant, R. Leaf area index estimates using remotely sensed data & BRDF models in a semiarid region. *Remote Sensing of Environment* **2000**, **73**, 18-30.

NOAA AVHRR. Advanced Very High Resolution Radiometer, 2011. Available online: http://noaasis.noaa.gov/NOAASIS/ml/avhrr.html. (accessed on Oct 11, 2013)

Chen, M.; Pavlic, G.; Brown, L.; Cuhlar, J.; Leblanc, S.G.; White, H.P.; Hall, R.J.; Peddle, D.R.; King, D.J.; Trofimow, J.A.; Swift, E.; Van der Sanden, J.; Pellikka, P.K.E. Derivation and validation of Canada-wide coarse-resolution leaf area index maps using high-resolution satellite imagery and ground measurements. *Remote Sensing of Environment***2002**, *80*, 165-184.

USGS. MODIS overview. Available online: http://modis-land.gsfc.nasa.gov/surfrad.htm (accessed on Oct 11, 2013)

Cohen, W.B.; Maiersperger, T.K.; Stith, T.G.; Tumer, D.P. An improved strategy for regression of biophysical variables and Landsat ETM+ data. *Remote Sensing of Environment***2003**, *84*, 561-571.

Fassnacht, K.; Gower, S.; MacKenzie, M.; Nordheim, E.; Lillesand, T. Estimating the leaf area index of north central Wisconsin forests using the Landsat Thematic Mapper. *Remote Sensing of Environment* **1997**, *61*, 229- 245.

Gupta, P. K.; Dutta, S.; Singh, R.; Raghuwanshi, N. S.; Panigrahi, S. Integration of remote sensing data into distributed hydrological model for irrigation command area management. Availabe online: http://www.watertech.cn/english/singh.pdf (Accessed on Oct 20, 2011).

White, J.D.; Running, S.W.; Nemani, E.; Keane, R.E.; Ryan, K.C. Measurement and remote sensing of LAI in Rocky Mountain montane ecosystems. *Canadian Forest Research* **1997**, *7*, 1714-1727.

Eklundh, L.; Harrie, L.; Kuusk, A. Investigating relationships between Landsat ETM+ sensor data and leaf area index in a boreal conifer forest. *Remote Sensing of Environment***2001**, *78*, 239-251.

SPOT. Available online: http://smsc.cnes.fr/SPOT/ (Accessed on Oct 11, 2013)

Phulpin, T.; Lavenu, F.; Bellan, M. F.; Mougenot, B.; Blasco, F. Using SPOT-4 HRVIR and VEGETATION sensors to assess impact of tropical forest fires in Roraima, Brazil. *International Journal of Remote Sensing* **2002**, *24*, 1943-1966.

Kraus, T.; Schmidt, M.; Dech, S.W.; Samimi, C. The potential of optical high resolution data for the assessment of leaf area index in East African rainforest ecosystems. *International Journal of Remote Sensing***2009**, *30*, 5039-5059.

Wu, J.; Shen, W.; Sun, W.; Tueller, P.T. Empirical patterns of the effects of changing scale on landscape metrics. *Landscape Ecology***2002**, *17*, 761–782.

Marceau, D.J.; Hay, G.J. Remote sensing contributions to the scale issue. *Canadian Journal of Remote Sensing***1999**, *25*, 357-366.

Rahman, A.F.; Gamon, J.A.; Sims, D.A.; Schmidts, M. Optimum pixel size for hyperspectral studies of ecosystem function in southern California chaparral & grassland. *Remote Sensing of Environment***2003**, *84*, 192-207.

Li, Z.,; Guo, X. A suitable vegetation index for quantifying temporal variation of leaf area index (LAI) in semiarid mixed grassland. *Canadian Journal of Remote Sensing***2011**, *36*, 709-721.

Fang, H.; Liang, S. A hybrid inversion method for mapping leaf area index from MODIS data: Experiments and application to broadleaf and needle leaf canopies. *Remote Sensing of Environment* **2005**, *94*, 405-424.

Doraiswamy, P.; Hatfield, J.; Jackson, T.; Akhmedov, B.; Prueger, J.; Stern, A. Crop condition and yield simulation using Landsat and MODIS. *Remote Sensing of Environment***2004**, *92*, 548-559.

Houborg, R.; Soegaard, H.; Boegh, E. Combining vegetation index and model inversion methods for the extraction of keyvegetation biophysical parameters using Terra and Aqua MODIS reflectance data. *Remote Sensing of Environment***2007**, 106, 39-58.

Choi, H.; Bindschadler, R. Cloud detection in Landsat imagery of ice sheets using shadow matching technique and automatic normalized difference snow index threshold value decision. *Remote Sensing of Environment***2004**, *91*, 237-242.

Wang, B.; Ono, A.; Muramatsu, K.; Fujiwara, N. Automated detection and removal of clouds and their shadows from Landsat TM images. *IEICE Transactions on Information and systems***1999**, *E82-D*, 453-60.

Tseng, D.C.; Tseng, H.T.; Chien, C.L. Automatic cloud removal from multi-temporal SPOT images. *Applied Mathematics and Computation***2008**, *205*, 584-600.

Barterretche, M.; Hudak, A.T.; Cohen, W.B.; Maierspenger, T.K.; Gower, S.T.; Dungan, J. Comparison of regression and geostatistical methods for mapping leaf area index with Landsat ETM+ data over a boreal forest. *Remote Sensing of Environment* **2005**, *96*, 49-61.

Twele, A.; Erasmi, S.; Kappas, M. Spatially explicit estimation of leaf area index using EO-1 Hyperion and Landsat ETM+ data: implications of spectral bandwidth and shortwave infrared data on prediction accuracy in a tropical montane environment. *GIScience& Remote Sensing* **2008**, 45, 1-20.

Deering, D.W.*Theory and Applications of Optical Remote Sensing*; Field Measurements of Bi-directional Reflectance; John Wiley & Sons, Inc., 1989. pp. 14-65.

Huete, A.R.*Theory and Application of Optical Remote Sensing*; Soil influences in remotely sensed vegetation-canopy spectra; Wiley, New York, USA, 1989. pp. 107-141.

Holben, B.N.; Justice, C.O. The Topographic Effect on Spectral Response from Nadir-Pointing Sensors. *Photogrammetric Engineering and Remote Sensing***1980**, *46*, 1191-1200.

Goel, N.S.; Thompson, R.L. Inversion of vegetation canopy reflectance models. IV. Total inversion of the SAIL model. *Remote Sensing of Environment***1984**, *15*, 237-253.

Meroni, M.; Colombo, R.;Panigada, C. Inversion of a radiative transfer model with hyperspectral observations for LAI mapping in poplar plantations. *Remote Sensing of Environment***2004**, *92*, 195-206.

Baret, F.; Clevers, J.; Steven, M. The robustness of canopy gap fraction estimates from red and near-infrared reflectances: A comparison of approaches. *Remote Sensing of Environment***1995**, *54*, 141-151.

Myneni, R.B.; Nemani, R.R.; Running, S.W. Estimation of global leaf area index and absorbed par using radiative transfer models. *IEEE Transactions in Geoscience & Remote Sensing***1997**, *35*, 1380-1393.

Kimes, D.S.; Nelson, R.F.; Manry, M.T.; Fung, A.K. Attributes of neural networks for extracting continuous vegetation variables from optical and radar measurements. *International Journal of Remote Sensing***1998**, *19*, 2639-2663.

Jacquemoud, S.; Bacour, C.; Poilve, H.; Frangi, J. P. Comparison of four radiative transfer models to simulate plant canopies reflectance: Direct and inverse mode. *Remote Sensing of Environment***2000**, *74*, 471-448.

Combal, B.; Baret, F.; Weiss, M.; Trubuil, A.; Mac´e, D.; Pragn`ere, A.; Myneni, R.; Knyazikhin, Y.; Wang, L. Retrieval of canopy biophysical variables from bidirectional reflectance using prior information to solve the ill-posed inverse problem. *Remote Sensing of Environment***2002**, *84*, 1-15.

Ji, L.; Peters A.J. Performance evaluation of spectral vegetation indices using a statistical sensitivity function. *Remote sensing of Environment* **2007**, *106*, 59-65.

Grinsted, A.; Moore, J.C.; Jevrejeva, S. Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Process in Geophysics***2004**, *11*, 561-566.

Brunsell, L.M.; Gillies, R.R. Determination of scaling characteristics of AVHRR data with wavelets: application to SGP97. *International Journal of Remote Sensing***2003**, *24*, 2945-2957.

Wang Q.; Adiku, S.; Tenhunen, J.; Granier, A.On the relationship of NDVI with leaf area index in a deciduous forest site.*Remote Sensing of Environment* **2005**,*94*, 244-255.

Zhu, H.; Li, Y.; Luo, T. MODIS-based distribution of leaf area index of grass land of Gonghe basin in Qinghai-Tibetan plateau. *Geoscience and Remote Sensing Symposium***2005,***5*, 3143-3145.

Xiao, X.; He, L.; Salas, W.; Li, C.; Moore, B.; Zhao, R.; Frolking, S.;Boles, S.Quantitative relationships between field-measured leaf area index and vegetation index derived from VEGETATION images for paddy rice fields. *International Journal of Remote Sensing***2002**, *23*, 3595-3604.