A Robust Approach for Estimating LAI from Landsat TM/ETM+ Imagery

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Abstract- **Leaf area index (LAI) is a quantitative measure of vegetation cover and of use in models of carbon, water and energy budgets. The recent availability of well-calibrated coverages of Landsat ETM+ imagery over large areas offers an opportunity for production of LAI estimates at fine spatial resolution. Empirical regressions between LAI and selected vegetation indices are applied to propagate uncertainties in calibration and atmospheric correction into LAI retrieval errors. Furthermore, the sensitivity to land cover mixtures is assessed by comparing retrievals with Landsat scale land cover with a 1km land cover product. A single Canada-wide composite of LAI derived from available Landsat ETM+ imagery is produced.**

I. INTRODUCTION

Leaf area index (LAI) is defined as half of the total surface area of foliage per unit ground area projected on the horizontal datum [4]. There have been previous initiatives to map LAI at the national scale using various space-borne sensors [1]. However, due to the large spatial variability that each ecozone contributes to these models and the high sensitivity of ecosystem model outputs to LAI, validation of these mapped products is required to gain knowledge of the random and systematic uncertainties. The research described in this document presents a robust methodology for LAI retrieval from Landsat data by assessing the uncertainties surrounding these estimates as they impact similar retrievals at coarser spatial resolutions.

II. OBJECTIVES

The objectives of this study are to:

1) Present an error budget for LAI retrievals using Landsat TM/ETM+ imagery.
2) Compare LAI uncertainties using two different vegetation indices ($\boldsymbol{SR} = \boldsymbol{TM}_4 / \boldsymbol{TM}_3$ and $\boldsymbol{IR} = \boldsymbol{TM}_4 / \boldsymbol{TM}_5$).
3) Produce a single Canada-wide composite of LAI derived from SPOT-VEGETATION (VGT) sensors based on cross-calibrated Landsat data.

III. DATA AND METHODOLOGY

A. *Scene Selection & Processing*

Twenty-two Landsat TM/ETM+ (hereafter referred to as TM or Landsat unless specification is warranted) scenes selected according to a stratified sampling of ecozones and land cover distributions were used in the error analysis. Ten of these scenes were coincident with surface measurements of LAI and were used as calibration data to derive the leaf area index algorithms [4]. All Landsat scenes were processed to at-sensor radiance values prior to the atmospheric correction procedure using header-file specific gains and biases. Landsat TM5 data were forward calibrated based on coefficients provided in [6]. Landsat ETM+ scenes were received from the data provider in the Level 1-G (systematically corrected) Hierarchical Data Format (HDF). The TM validation scenes were geometrically corrected to scene-specific coordinates supplied with the data.

Atmospheric correction was performed using 6S [7]. The standard continental aerosol model was used for all scenes except the Maritime scenes (Paths=08,09,10) which instead used the maritime model. Scene-centre elevation was obtained from topographic data at a scale of 1:50000. Ozone and water vapour concentrations were extracted from AVHRR 10-day composites [2]. Aerosol optical depth (AOD), considered the most critical input parameter, was estimated from the dense, dark vegetation (DDV) approach [5]. The DDV procedure was modified into an iterative method as summarized below and described in [3]. Using an initial seed value of AOD=0.1, top-of-canopy NDVI was used to determine DDV targets based on two criteria. The first criterion was top-of-atmosphere $1\% > \rho_{2.2\mu m} < 5\%$ (where ρ is reflectance with wavelength subscript). The second criterion was a top-of-canopy NDVI>90^{th} percentile. By using the initial seed value for AOD, this NDVI was thought to be more robust than the more commonly used estimate of top-of-atmosphere NDVI. LAI maps were then generated based on land cover (LC) type and land use, using empirical regressions to either the simple ratio (***SR***) or the infrared simple ratio (***IR***) vegetation index (VI) as discussed in [4].

B. *Error Analysis*

Three separate error analyses were performed in this study to assess the uncertainties of the operational variables used to derive a TM-based LAI product and a coarse-scale product from cross-calibration of TM based regressions (consult [4] for the coarse-scale error budget). The first trial quantifies the errors due to using a 1km LC input to the algorithm rather than the fine-scale TM input. The 1km LC input was based on a coarse-scale classification map [4]. The resultant errors will address the limitation of using a more generalized 1km-scale land cover layer for LAI retrieval. Error trials 2 and 3 quantify the impact of TM atmospheric correction errors on LAI. The error budget within a TM-based LAI product of uncorrelated components is shown in (1), where N is the normal distribution. Uncorrelated components representative of the total bias and random errors are further decomposed in (2) and (3), respectively.

$$\varepsilon_{LAI} \approx N(\delta_{LAI}, \sigma_{LAI}) \qquad (1)$$

where $\delta_{LAI} = (\delta_{ALG} + \delta_{VI})$ (2)

represents the systematic error and,

$$\sigma_{LAI}^2 = (\sigma_{ALG}^2 + \sigma_{VI}^2) \qquad (3)$$

represents the random error.

Firstly, to assess the algorithm (subscript $_{ALG}$) uncertainty we must break it down into: a) regression error, b) land cover error and c) spatial scaling error. Structural regression errors for ***SR*** and ***IR*** are about +/- 1 LAI unit [4], however this error is similar to the coarse-scale algorithms which will cancel out at the >1km-scale. Errors due to land cover misclassification are assumed to be negligible at the 30m-scale and are measured at 1km-scale in Trial 1 of this study. The spatial scaling errors can contribute relative LAI errors of 30% as documented in [4], however, such errors are spatially random and become negligible at spatial resolutions >3km. To assess the impact of the vegetation index error, the VI terms in (2) and (3) can be decomposed into: a) radiometric calibration error and b) atmospheric correction & BRDF error. The radiometric calibration error for ETM+ scenes (and cross-calibrated TM scenes) was stated to be 1-2% in [4]. The BRDF variability was assumed to be quantified in the algorithm regression residuals and the atmospheric correction errors at the 30m-scale are further decomposed as shown in (4) and (5).

$$\delta_{ATCOR} = (\delta_{DDV\,REF} + \delta_{3/7\,RATIO}). \qquad (4)$$

$$\sigma_{ATCOR}^2 = (\sigma_{DDV\,REF}^2 + \sigma_{3/7\,RATIO}^2). \qquad (5)$$

The mean $\rho_{0.64\mu m}$ of DDV targets was propagated to +1sigma in Trial 2 to evaluate the sensitivity of this variable on the atmospheric correction procedure. The second component in (4) and (5) was tested in Trial 3. Since many users of the DDV approach for AOD determination rely on a constant ratio between $\rho_{0.64\mu m}$ and $\rho_{2.2\mu m}$ [5], the uncertainty in this assumption was thought to be an important assessment. To test this uncertainty, scenes were atmospherically corrected once using the AOD as determined from the DDV-constant ratio method and then recorrected using the AOD determined from a modified DDV-variable ratio method. Input data for the latter method is shown in Fig. 1 and was provided from the BOReal Ecosystem-Atmosphere Study (BOREAS)[8]. These data permit the extension of the constant ratio in [5] over a variety of top-of-canopy NDVI values as shown in (6).

$$\rho_{0.64\mu m} / \rho_{2.2\mu m} = NDVI*(-1.2493)+1.4. \qquad (6)$$

Root-Mean-Square (RMSE) errors representing precision uncertainty, and Relative Absolute errors (RAE) indicating systematic uncertainties were then calculated for the resultant LAI maps.

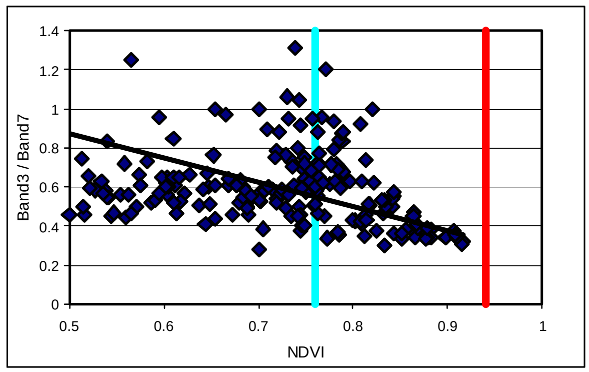

Figure 1-Regression plot of TM_3 / TM_7 Vs. NDVI based on MMR top-of-canopy reflectance values. Black line is presented in (6), blue line shows minimum NDVI of DDV targets and the red shows the maximum.

IV. RESULTS

Precision uncertainties in LAI as a function of vegetation index for the tested trials are presented in Table 1. All precision errors measured for LAI fields derived from ***SR*** were much larger than LAI derived from ***IR***. RMS errors in LAI from ***SR*** due to land cover scaling and DDV reflectance uncertainties are approximated to be 1.41-1.59 LAI units, whereas the precision in the DDV ratio uncertainty is 0.66. Errors in LAI from ***IR*** are reduced substantially in all cases.

TABLE 1
MEAN AND {MAX} RMSE LAI PRECISION ERRORS FOR EACH TRIAL ON ***SR*** & ***IR*** OVER ALL SCENES.

	Trial 1 - LC	Trial 2 - DDV ref	Trial 3 - DDV ratio
SR	1.59 {2.43}	1.41 {3.24}	0.66{1.84}
IR	0.92 {1.52}	0.41 {1.76}	0.17{0.86}

The mean systematic error estimates of LAI are presented in Table 2. The highest RAE's were noticed in Trial 1, where the mapped LAI could have a relative error of approximately 34% for ***SR*** and 23% for ***IR***. This result shows the impact of using a 1km land cover product to derive fine-scale LAI. RAE's associated with the two atmospheric correction components were calculated as approximately 21% and 11% for LAI derived from ***SR*** and 5% and 3% for LAI derived from ***IR***.

TABLE 2
MEAN AND {MAX} RAE (%) LAI ACCURACY ERRORS FOR EACH TRIAL ON ***SR*** & ***IR*** OVER ALL SCENES.

	Trial 1 - LC	Trial 2 - DDV ref	Trial 3 - DDV ratio
SR	34 {52}	21 {50}	11 {29}
IR	23 {42}	5 {21}	3 {9}

V. DISCUSSION

The purpose of this study was to present an error budget for LAI retrievals at the 30m-scale. Relative LAI errors from DDV reflectance uncertainty were approximated at 11-21% for ***SR*** and at 3-5% for ***IR***. This implies that larger absolute errors occur for higher LAI values; chiefly due to their lower absolute reflectance in red and SWIR wavelengths. The DDV ratio between $\rho_{0.64\mu m}$ and $\rho_{2.2\mu m}$ produced a relative error of 11% for ***SR*** and 3% for ***IR*** generated LAI fields. RMSE values are typically < l LAI unit for ***IR*** trials. Total LAI error at the 30m-scale is derived from the Euclidean sum of RMSE values and is approximately 0.75 LAI units using the ***IR*** vegetation index. LAI is less precise when examining trials based on ***SR*** calculations. Precision errors in LAI are almost twice as large for ***SR*** trials over ***IR*** trials. Given the results presented in this study and in [4], ***IR*** seems to be a more robust estimator of LAI than ***SR*** primarily due to the lack of atmospheric effects in $\rho_{1.5\mu m}$ compared to $\rho_{0.64\mu m}$.

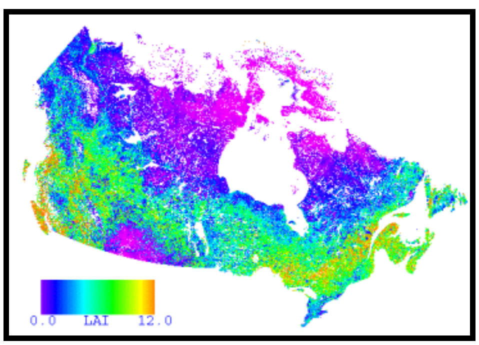

Figure 2 – Canada-wide LAI product. July 21-31, 2000.

Fig. 2 provides a representation of a synthesis of both fine and coarse resolution LAI estimates over Canada. The coarse scale estimate is derived from the SPOT VGT sensors as in [4]. The level of uncertainty and spatial resolution of these estimates will vary with data source.

VI. CONCLUSION

A robust estimation of Landsat-scale retrieval of LAI has been proposed with the inclusion of uncertainty values in land cover scaling for adaptation to coarser resolution sensors. Such approaches need to be explored to generate a better understanding of the uncertainties in both fine and coarse-scale LAI products. Furthermore, an initial assessment of potential errors in LAI from the DDV approach to atmospheric correction is included. These need to be examined further with special care given to errors in DDV reflectance. The land cover scaling trial produced the largest systematic error in LAI. Therefore, a recommendation is put forth to use a fine-scale land cover product to derive 30m-scale LAI whenever it is feasible to do so.

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