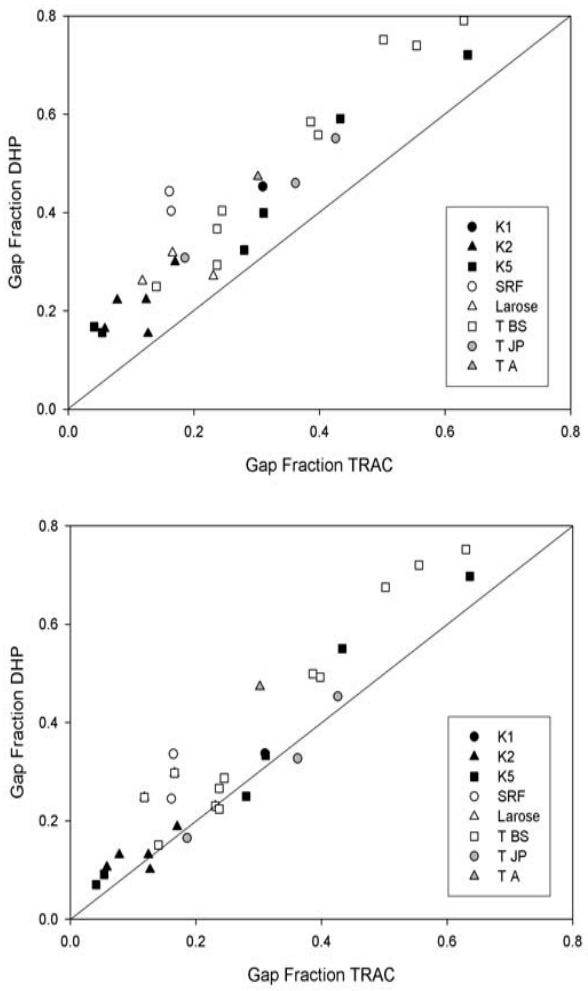
From Validation to Calibration

- Clumping Issues
- Unbiased Regressions in presence of errors
- Why fewer bands may be better
- Evaluating MODIS 250m and MERIS 300m products
- Calibration

DHP vs TRAC



Leblanc et al. AFM, 2005

DHP vs LAI-2000

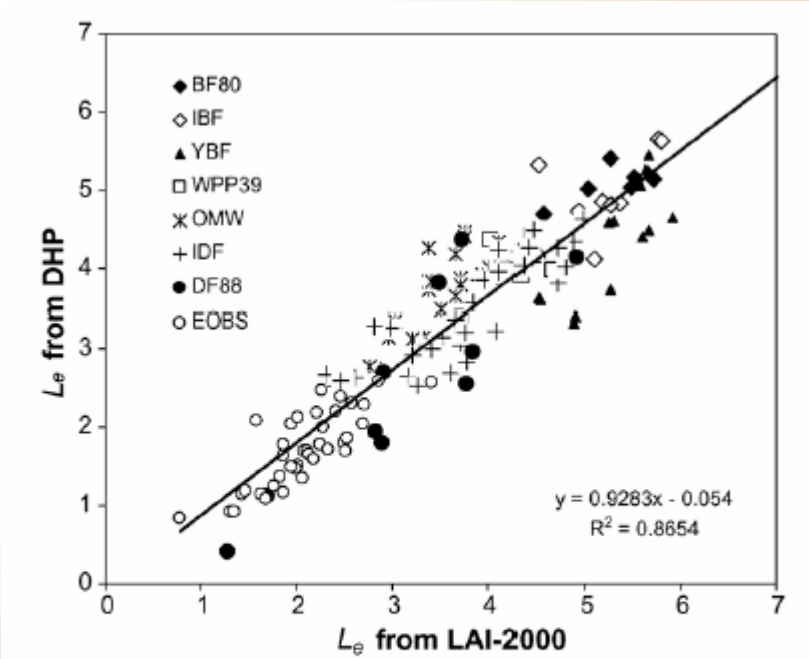
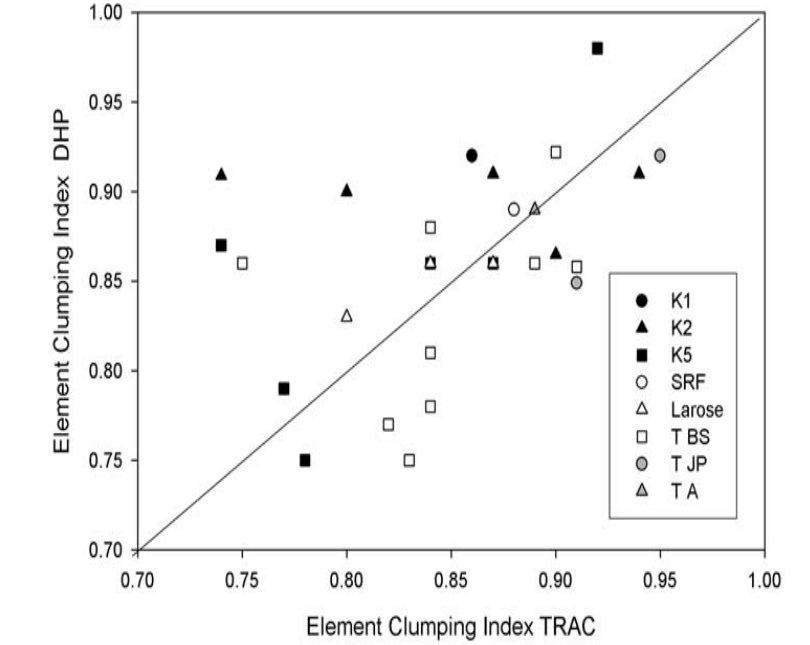


Fig. 2. Comparison of effective LAI (L_e) values measured using the digital hemispherical photography (DHP) technique with those measured using LAI-2000.

Chen et al. AFM, 2006

TRAC vs DHP Clumping



Leblanc et al. AFM, 2005

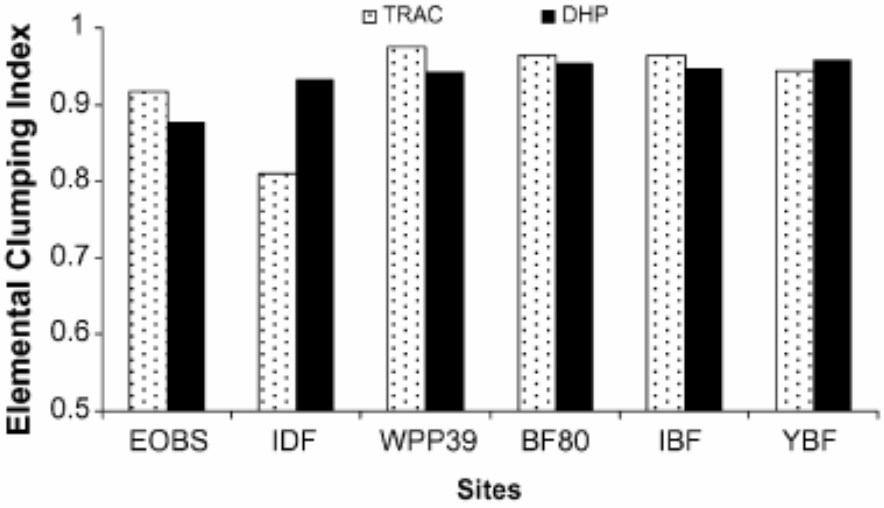
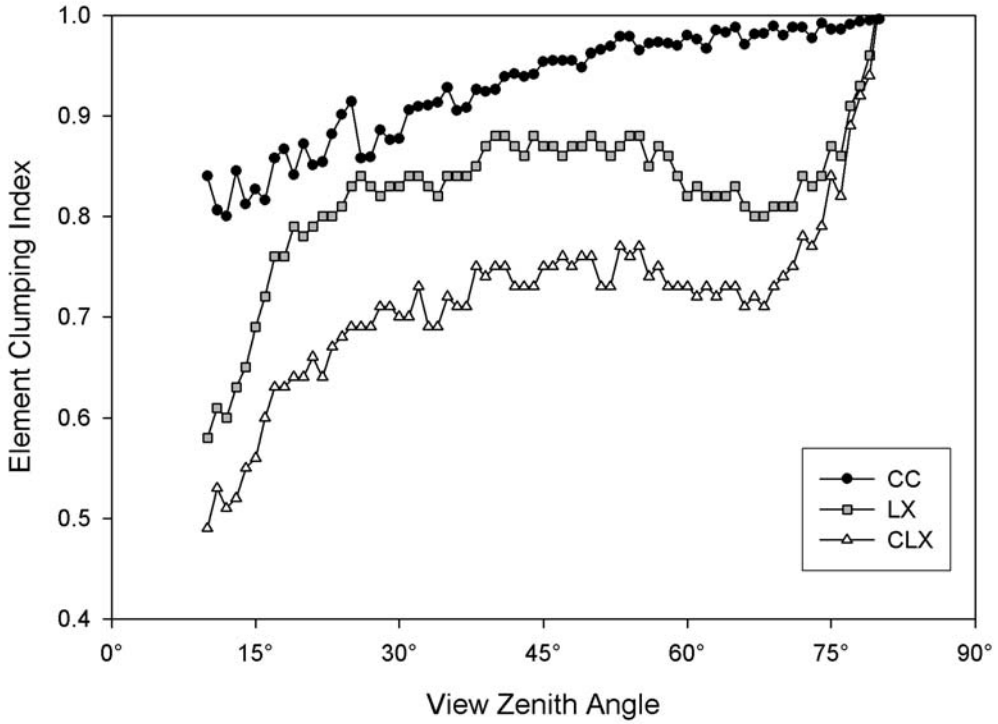


Fig. 3. Comparison of the element clumping index measured using the digital hemispherical photography (DHP) technique with those measured using TRAC.

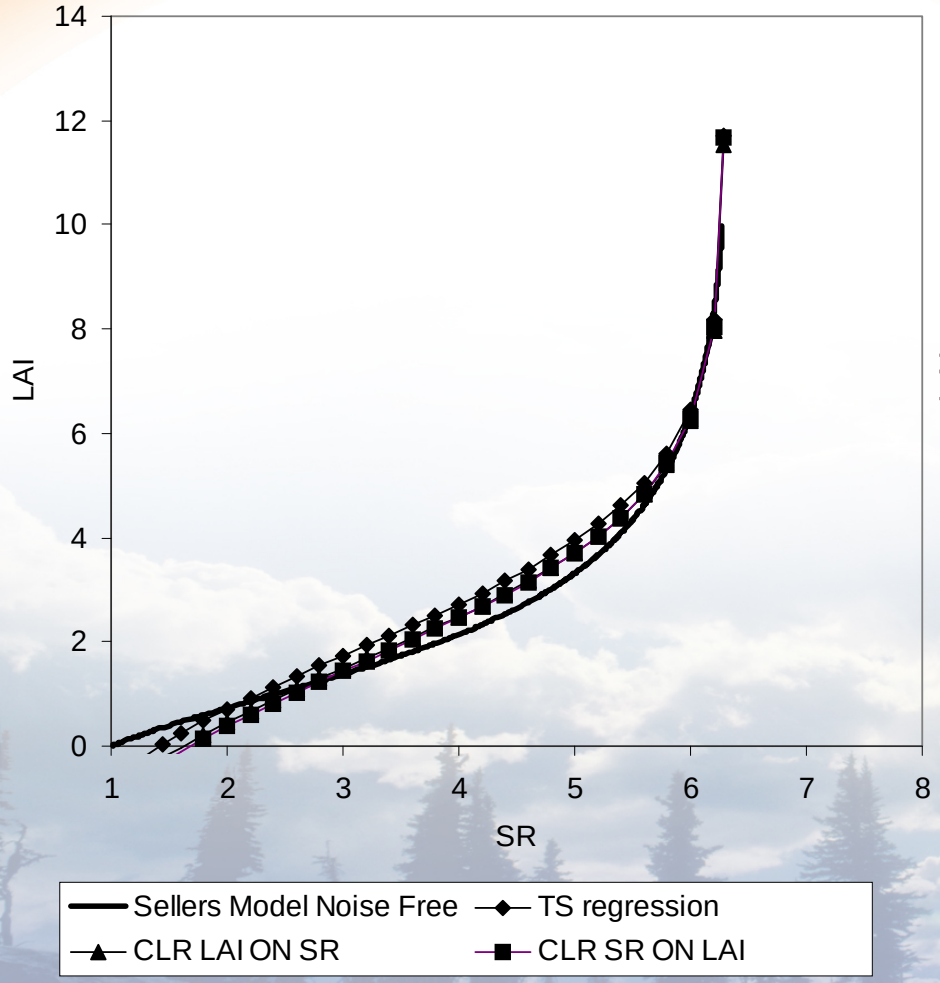
Chen et al. AFM, 2006

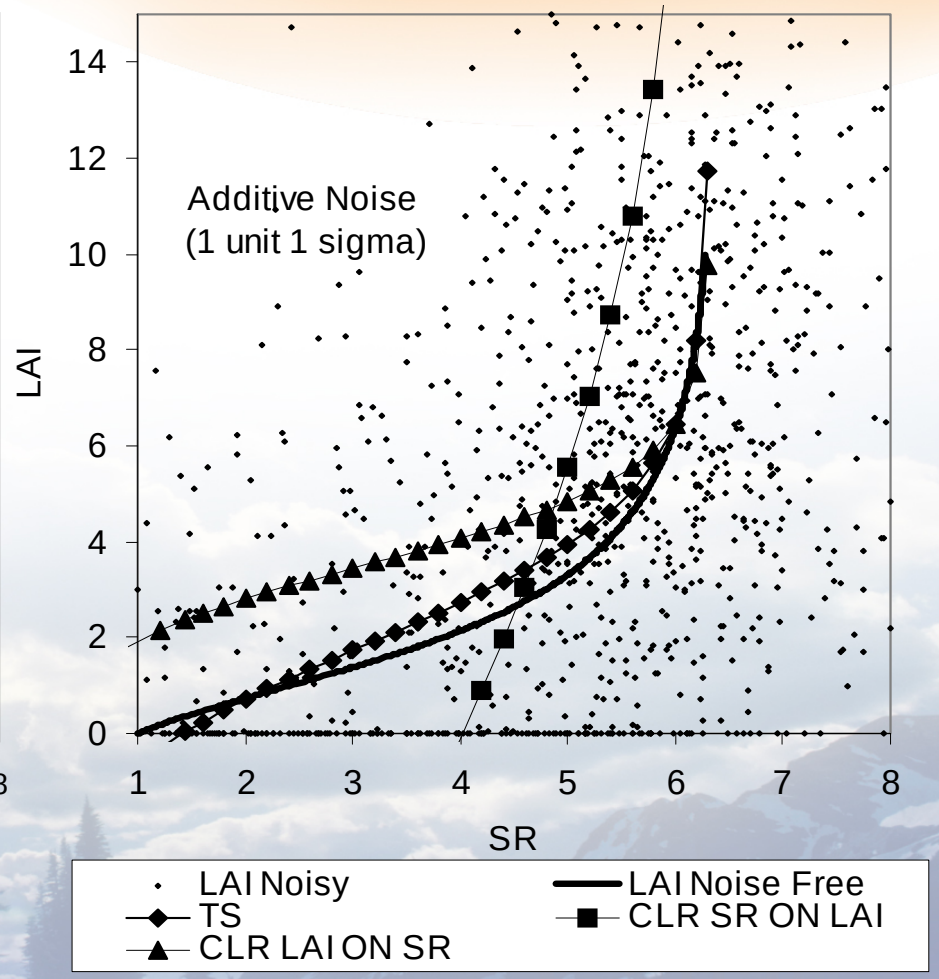
Lang vs CC Clumping



Leblanc et al. AFM, 2006

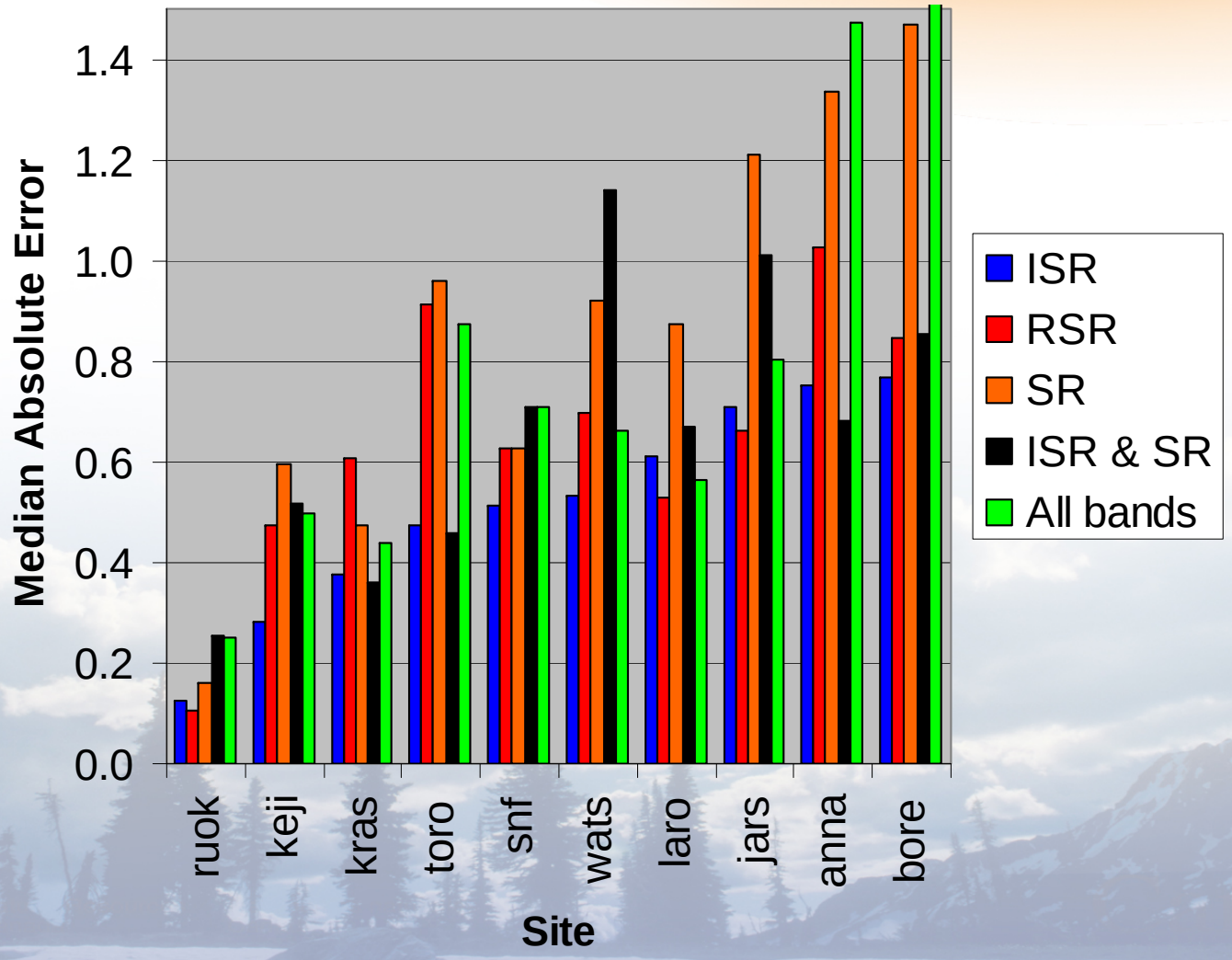
Appropriate Linear Regression



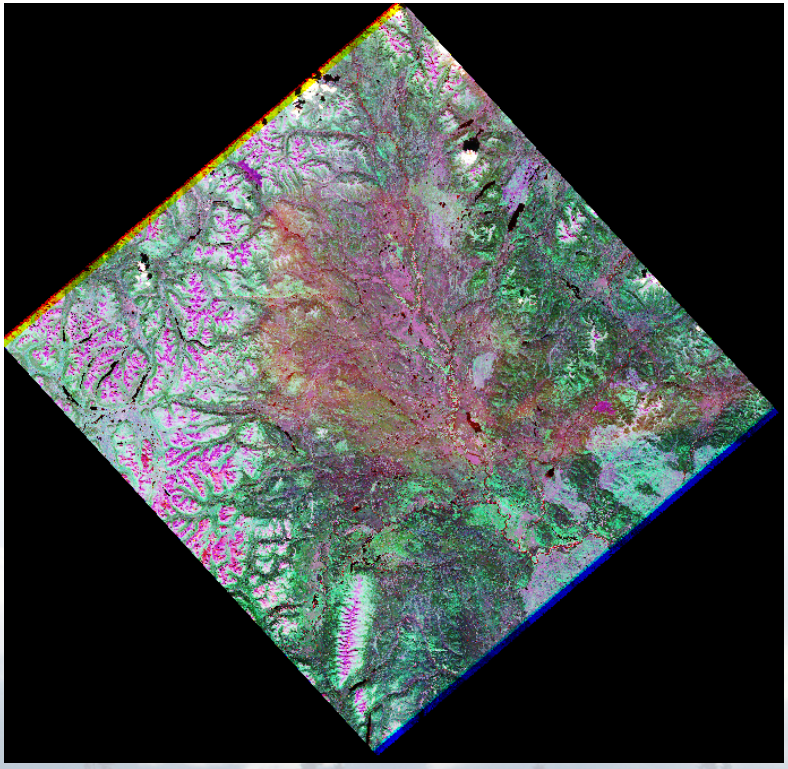


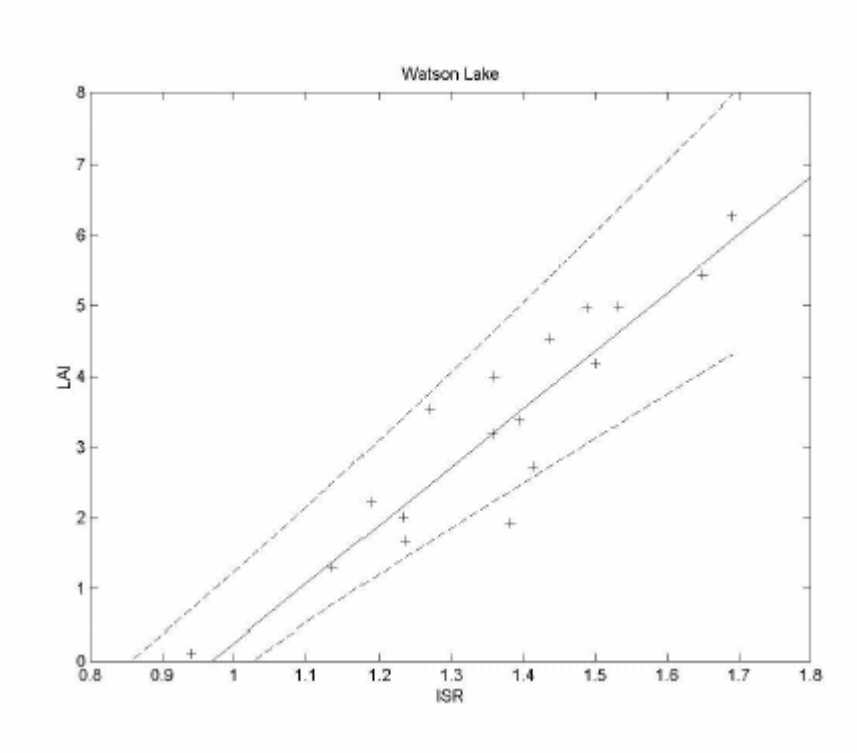
Fernandes et al., RSE 2006

Do we need all bands?



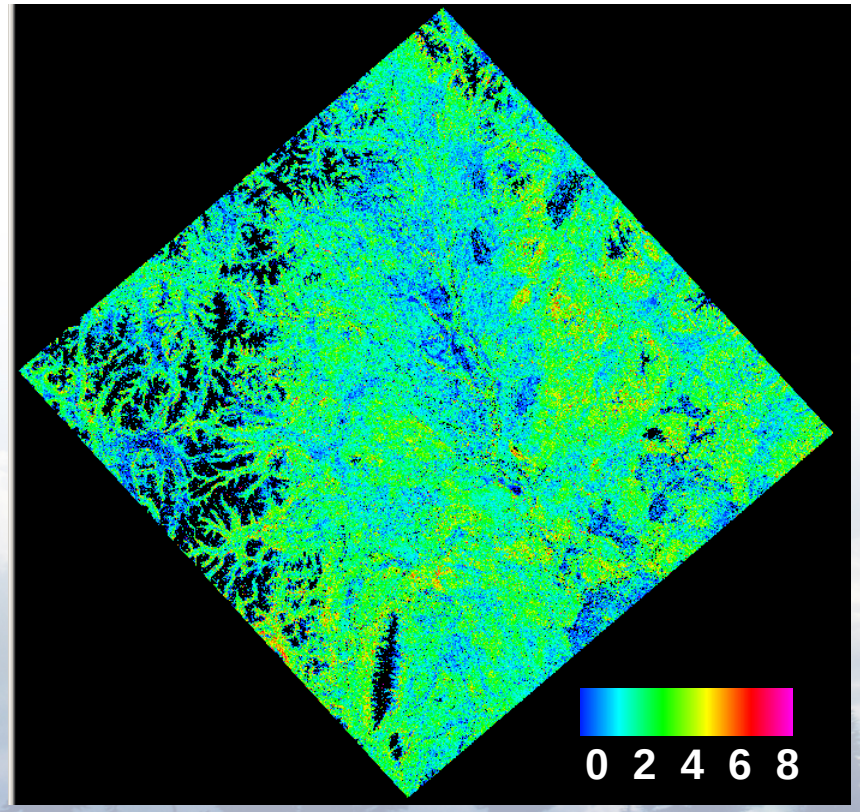
Why simple tranfer fn. may be better





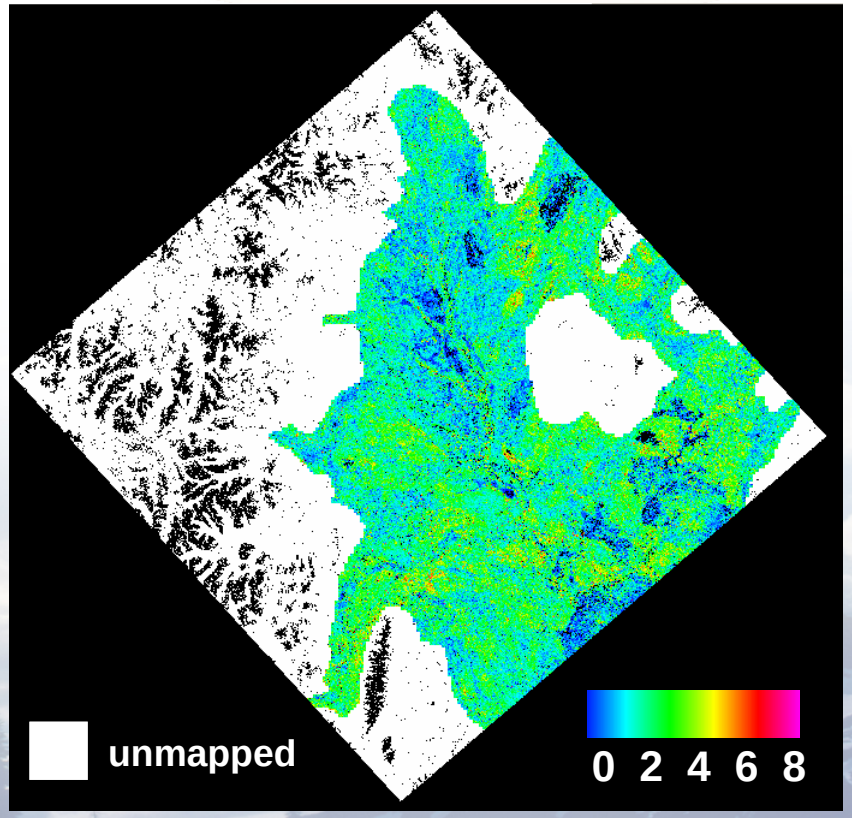
Mappable Area

LAI = f(ISR)



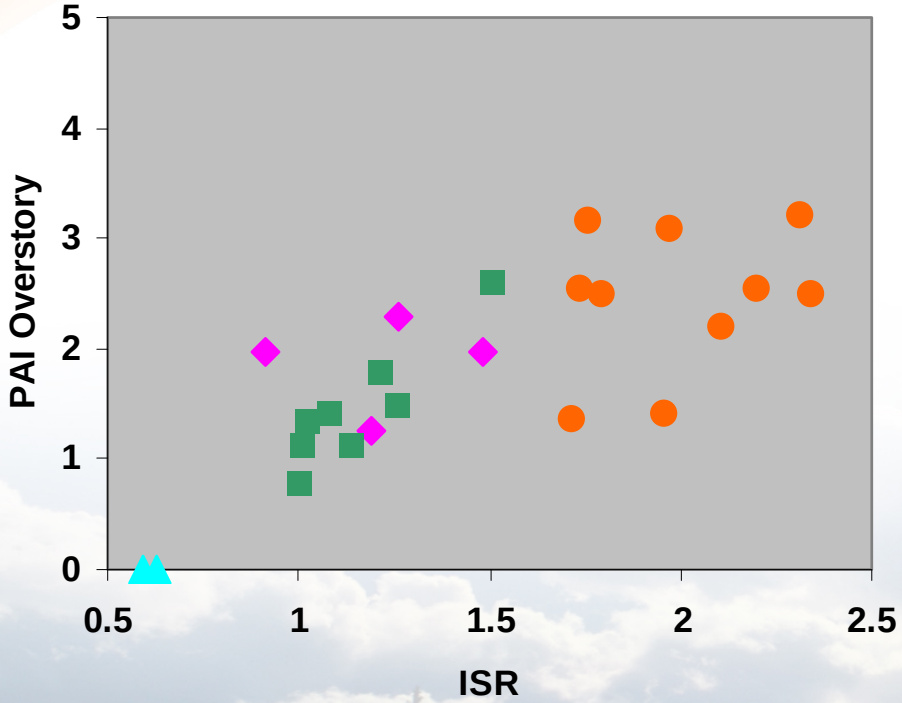
M.A.E.=0.37

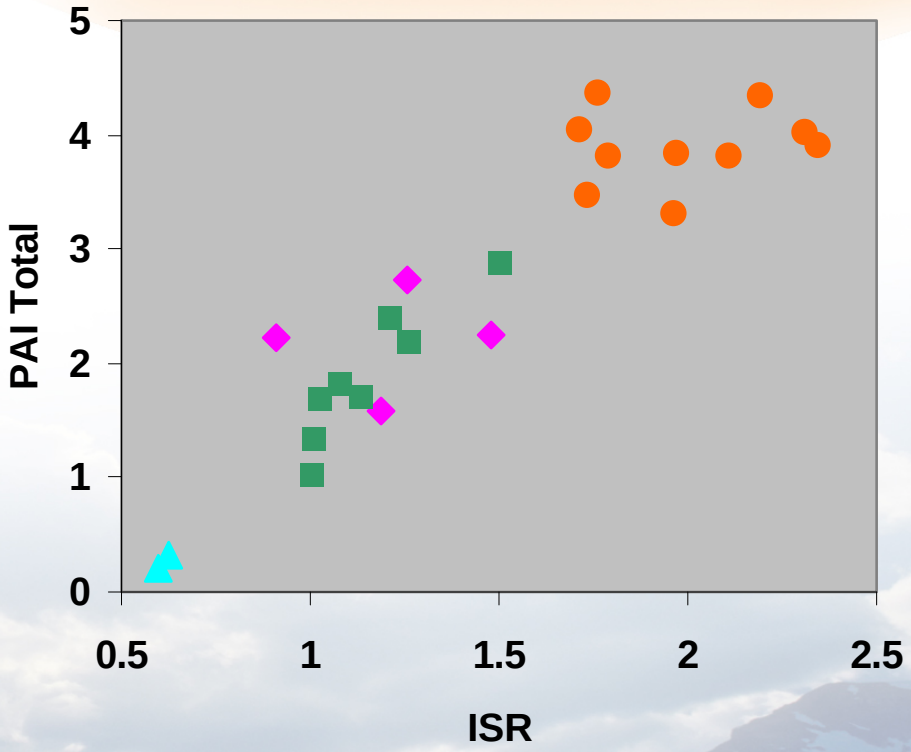
LAI = f(B03,B04,B05)



M.A.E.=0.35

Do not forget understory!



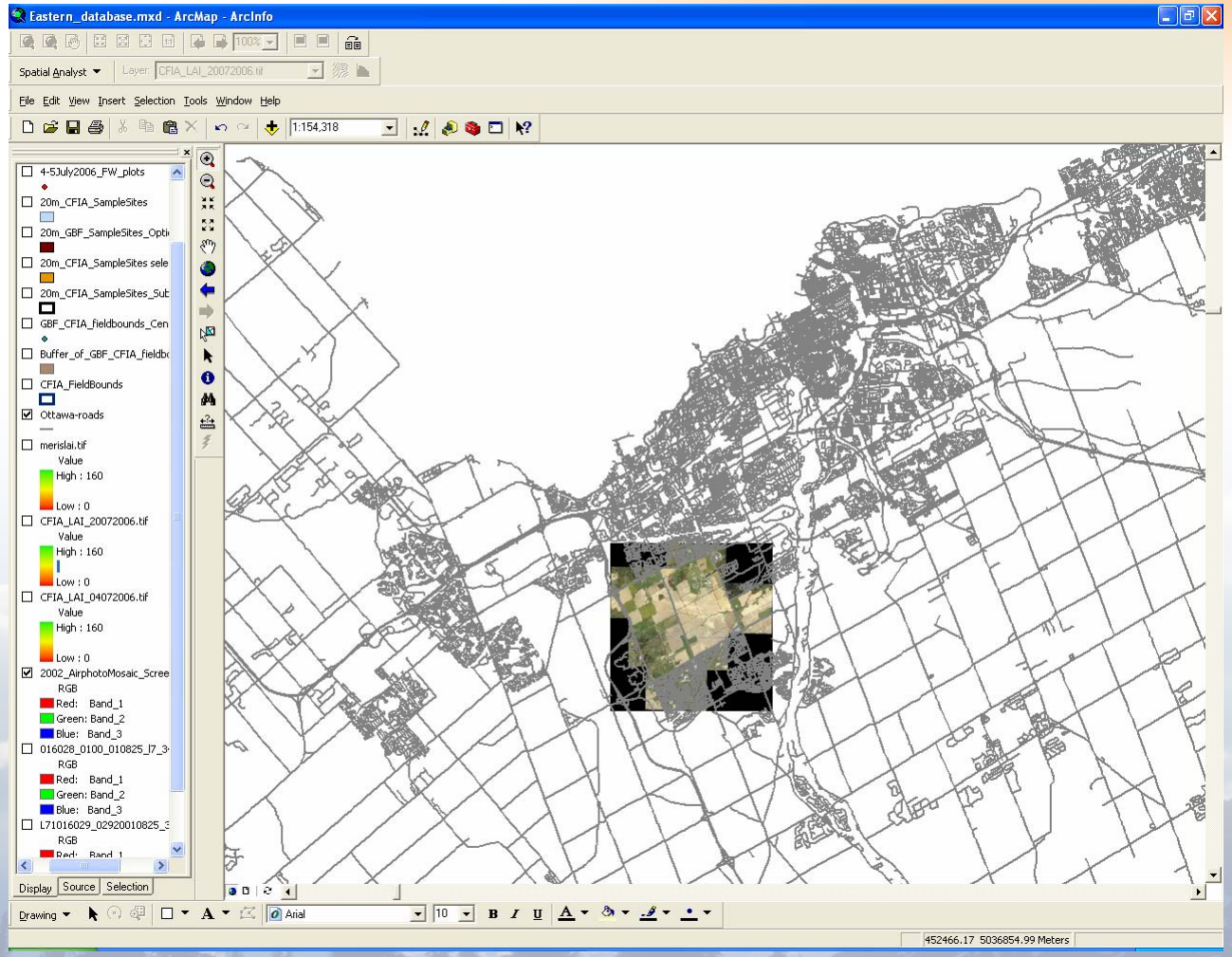


Ponderosa Pine
Shrubs
Orchards
Vineyards

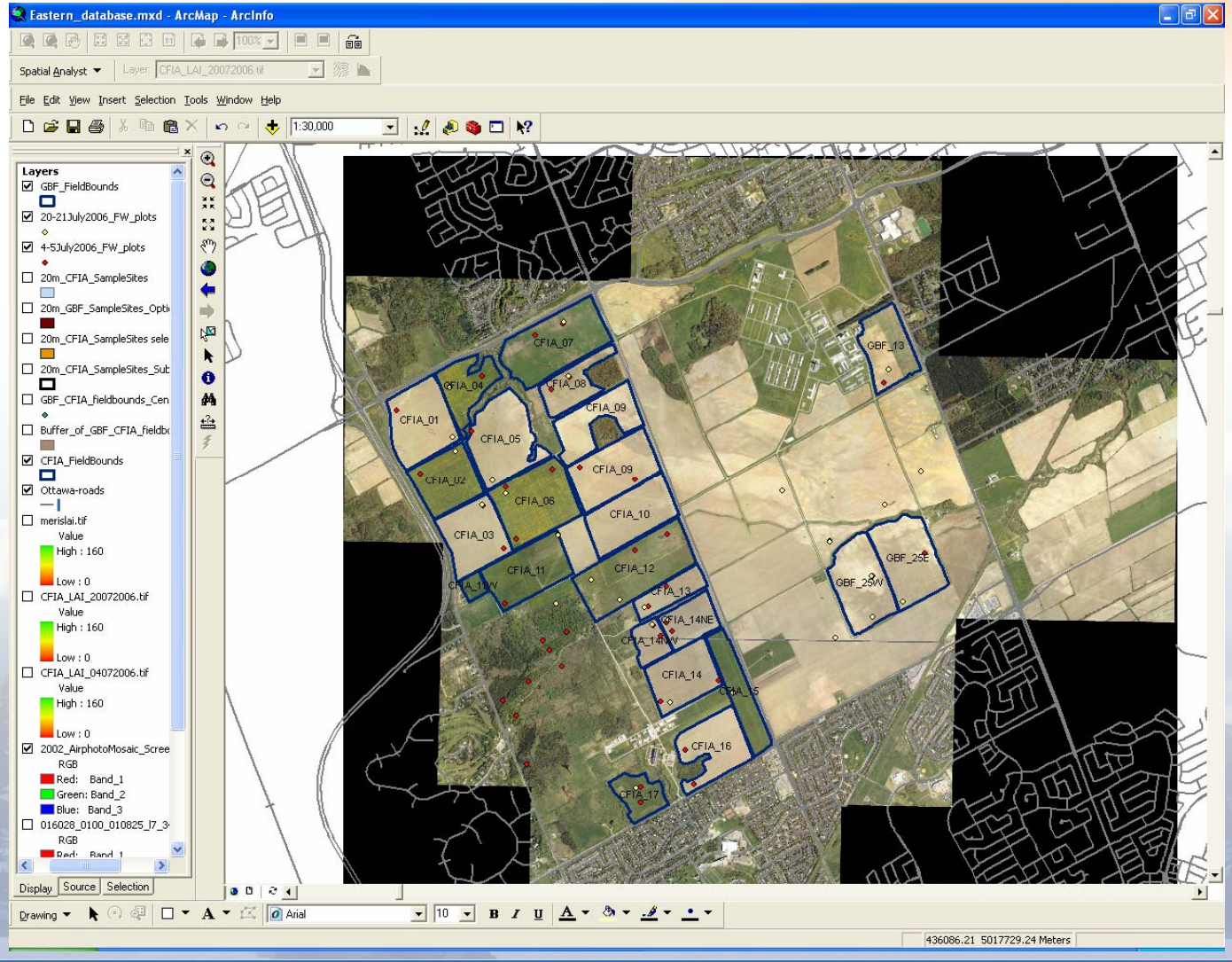
Current Issues

- Dense short grasses
  - Use beer's law with near nadir rings
  - Use G function assumed from all rings
  - Requires at least double sampling
- Quality control/error budget
  - Precision error of plot mean LAI:
  - Bias error in plot mean LAI
  - Consider duplicating transects in ESU's where spatial footprint is small (e.g grasses)
- Woody area
  - Mask trunks but leave other woody area
- Do we need to correct for shoot clumping with new cameras that resolve high resolution mixed pixels?

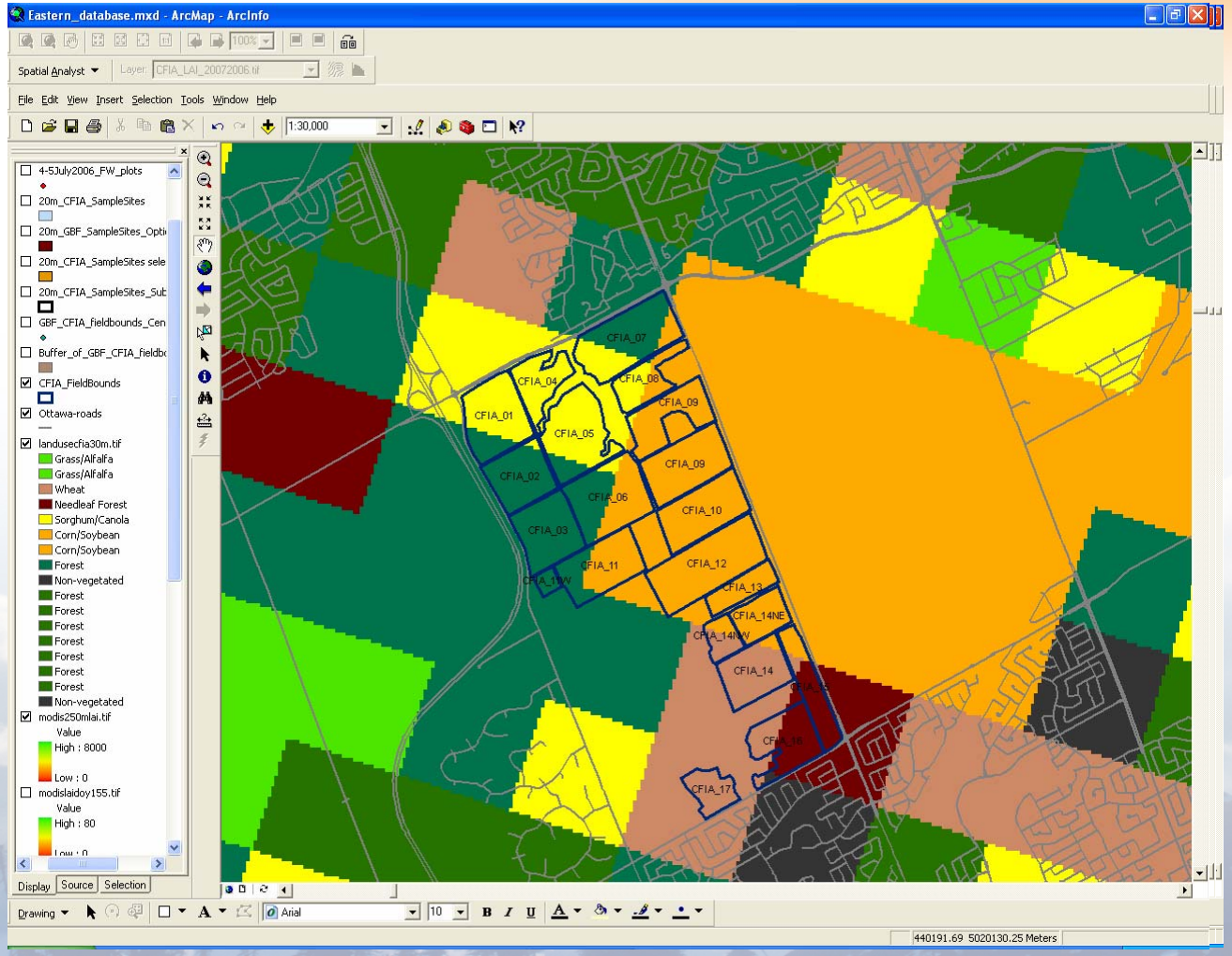
Study Area – Central Food Inspection Agency Ottawa (AAFC)



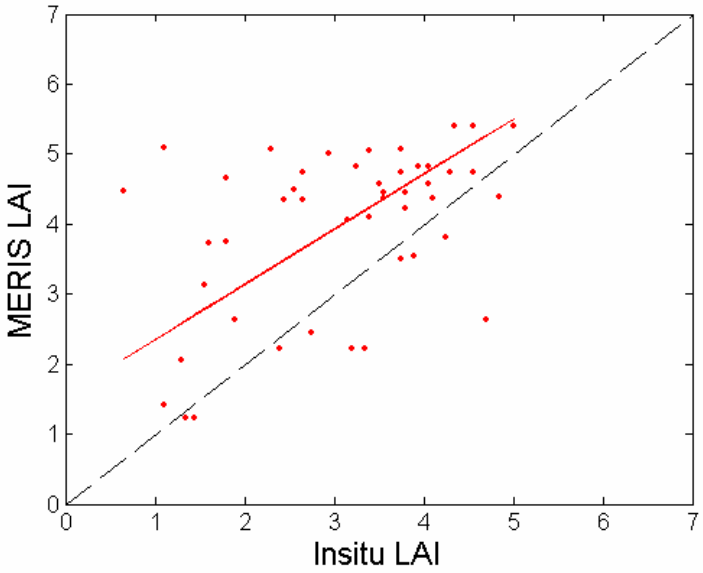
Study Area – Central Food Inspection Agency Ottawa (AAFC)



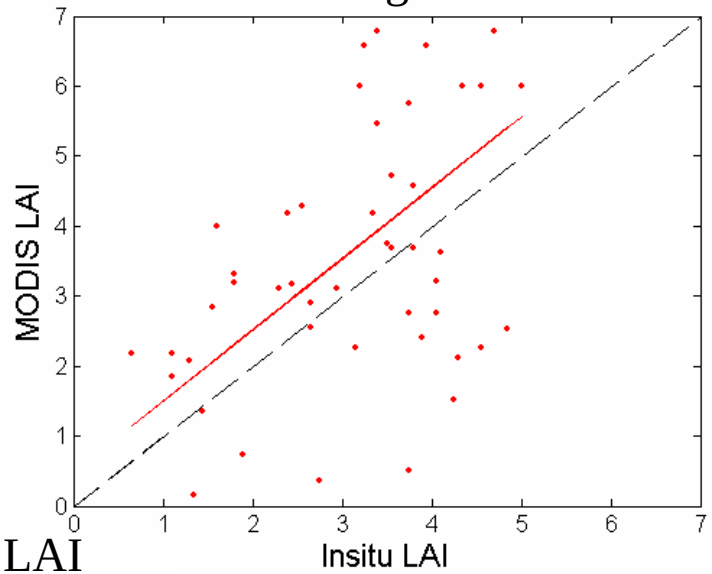
LAI July 4-5, 2006



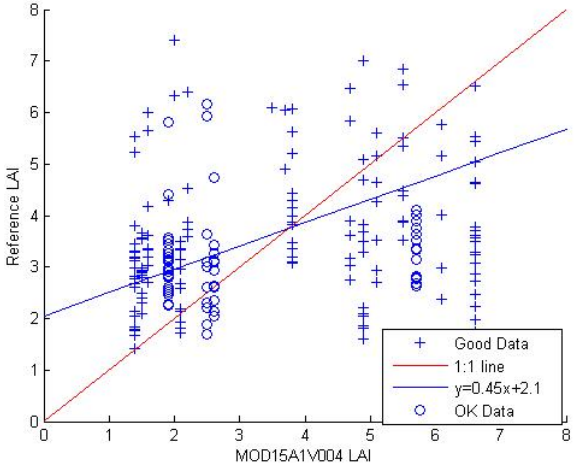
CYCLOPES LAI using MERIS FR



CCRS LAI using MODIS 250m



MOD15A1 V004 LAI



Calibration!

- Model: $Y = f\left(\begin{bmatrix} \underline{x}_o \\ \underline{x}_u \end{bmatrix}\right)$
- state variables
  - Observable: e.g. $\underline{x}_o = [LAI]$
  - Unobservable: e.g. $\underline{x}_u = [\rho_s, \rho_v, \tau_v, h, r, h_b, n_c, \ldots]$
  - Model f can be stochastic or specified with output pdf
- Outputs: reflectances y
- Inverse problem: $p(\underline{x} \mid Y) = \int_{\forall x^*} p(\underline{x} \mid Y, \underline{x}^*) P(Y) P(\underline{x}^*) dx^*$
- Need a priori pdf $P(\underline{x}^*)$

- Prior probability of state variables

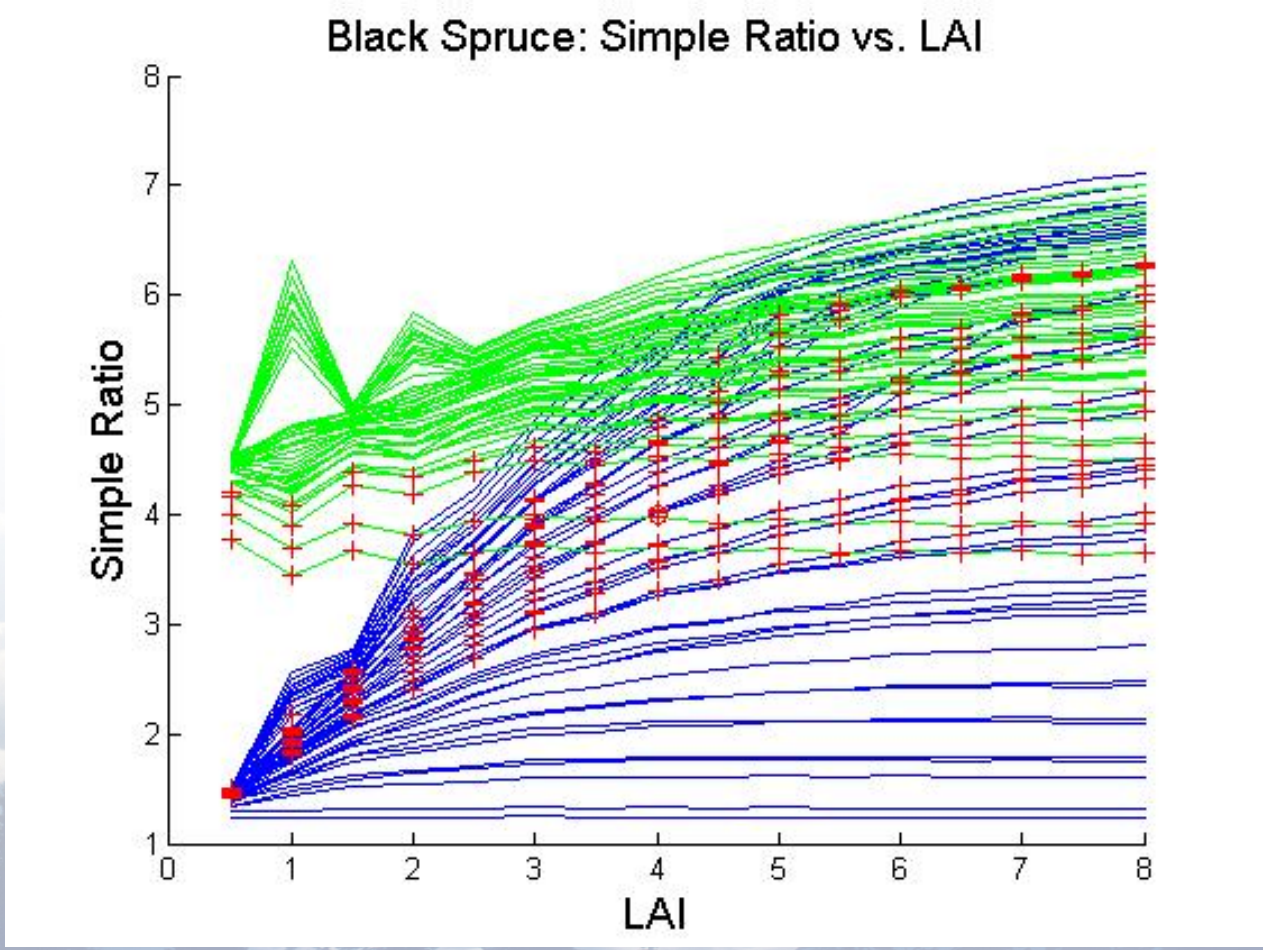
$$P\left(\underline{x}^{*}\right)=\int_{Y}\int_{\forall \underline{x}} p\left(\underline{x}\middle|\underline{x}_{o},Y\right)P\left(\underline{x}_{o},Y\right)d\,\underline{x}_{o}d$$

- Prior probability of observables by density estimation from cal/val dataset

$$P\left(\underline{x}_{o},Y\right)$$

- Estimation of conditional probability of unobservables:

$$P\left(\underline{x}\middle|\underline{x}_{o},Y\right)=\frac{p\left(\underline{x}_{o},Y\middle|\underline{x}\right)P\left(\underline{x}\right)}{\int_{\forall \underline{x}} p\left(\underline{x}_{o},Y\middle|\underline{x}\right)P\left(\underline{x}\right)dx}$$


Black Spruce: Simple Ratio vs. LAI
Simple Ratio
LAI
1
2
3
4
5
6
7
8
0
1
2
3
4
5
6
7
8

Calibration Concept

- Relies on reasonable sampling of observables.
- Relies on estimates of errors in observables and model.
- Flexible with respect to types of a priori pdf's.
- Can be used with multiple forward/inverse models including neural network.
- Observables could include "finer" resolution LAI fields if error bars are known.
- Concern with matching observables to closely should be accounted for with initial prior estimate.