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Short communication

Leaf area index uncertainty estimates for model–data fusion applications

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ABSTRACT

Estimates of data uncertainties are required to integrate different observational data streams as model constraints using model–data fusion. We describe an approach with which random and systematic uncertainties in optical measurements of leaf area index [LAI] can be quantified. We use data from a measurement campaign at the spruce-dominated Howland Forest AmeriFlux site for illustrative purposes. We made measurements along two transects (one in a mature stand, one in a recently harvested shelterwood) before sunset on successive days using both the Li-Cor LAI-2000 plant canopy analyzer and digital hemispherical photography (DHP). The random measurement uncertainty (1σ) at a given point for a single measurement is about 5% for LAI-2000 and 10% for DHP. These uncertainties are small compared to potential systematic biases due to instrument calibration errors and data processing decisions, which are estimated to be 10–20% for each instrument. Sampling uncertainty (due to the spatial variability along each transect where we conducted our measurements) is an additional, but again relatively small, uncertainty. Assumptions about clumping parameters, for which standard literature values are typically used, remain large sources of uncertainty. This analysis can also be used to develop strategies to reduce measurement uncertainties.

1. Introduction

The model–data fusion approach essentially combines a *process-based model structure* with *observational constraints* and an *optimization routine* with which model parameters and states, and their respective uncertainties, are estimated conditional on the data (Raupach et al., 2005; Williams et al., 2005, 2009). Inverse analyses conducted in this manner are thus a combined product that leverages the structure of the model as well as the information content of data, thereby improving on more conventional model-only or data-only approaches. Central to model–data fusion are techniques that permit full propagation of data and model uncertainties in a thorough and statistically defensible manner (e.g., Richardson et al., 2010); thus model predictions can be reported not just as a single value but as a range of values (i.e., the confidence limits) within which the "true" value is expected to fall. This information is required for risk assessment, decision support, and other policy-relevant applications.

A range of different types of data may be used as observational constraints. For example, with carbon [C] cycle models, information on both ecosystem state variables (e.g., measurements of C stocks or pools: above- and below-ground biomass C, organic and mineral soil C) and associated rates of change (e.g., measurements of C fluxes: photosynthesis, autotrophic and heterotrophic respiration, litterfall) can be incorporated within the model–data fusion framework. However, this requires uncertainty estimates ($\sigma_{i,j}$) for each observation y of data stream i at time j ($y_{i,j}$). In the standard approach (Raupach et al., 2005), observations are weighted according to our confidence in the data (i.e., as $1/\sigma_{i,j}^2$ in weighted least squares optimization) so that observations in which we have more confidence exert greater influence on the outcome of the analysis. As (Raupach et al., 2005) noted emphatically, "[g]iven the importance of data uncertainties, there is an urgent need for soundly based uncertainty characterizations for the main kinds of data used in terrestrial carbon observation".

Methods to quantify the time-varying nature of uncertainty in ecosystem-scale measurements of carbon, water and energy fluxes have been developed (e.g., Hollinger and Richardson, 2005; Richardson et al., 2006), and similar approaches have been applied to chamber-based measurements of soil respiratory fluxes (Savage et al., 2008). Uncertainties in forest inventory and ecosystem carbon and nutrient budget calculations have been investigated by Chave et al. (2004), Harmon et al. (2007), and Yanai et al. (2010). However, for many other types of ecosystem measurements, rigorous uncertainty estimates (or methods to obtain these estimates) have not been presented in the literature.

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One such ecosystem parameter lacking adequate uncertainty estimates is leaf area index (LAI). LAI is a measure of carbon allocation to photosynthetic organs, as well as the potential for light interception by the canopy (Chen et al., 1997; Gower et al., 1999; Breda, 2003). Accurate assessment of LAI is essential for scaling leaf-level measurements to canopy-level; both Bonan (1993) and Williams et al. (2001) demonstrated that model-based productivity estimates were extremely sensitive to LAI. The seasonal dynamics of LAI also provide information about phenological processes of development and senescence.

Here we present results from a LAI measurement campaign at a spruce-dominated forest in north-central ME, USA. We use these data to derive estimates of the potential random and systematic measurement errors in leaf area index measured using two widely used instrument-based optical techniques. Our objective is to document this approach to quantifying LAI measurement uncertainty, so that these uncertainties can be accounted for when LAI data are used as observational constraints in future model–data fusion efforts.

2. Methods

2.1. Study site

The Howland Forest (45.20°N, 68.74°W) is located in central Maine at the southern ecotone of the North American boreal zone that extends north and west from Maine across thousands of kilometers. The forest at Howland is generally classified as "spruce-fir" type and consists of red spruce, and eastern hemlock, which together account for over 70% of the tree biomass. Topography is flat to gently rolling. The site is a member of the AmeriFlux network, and eddy covariance measurements of carbon, water and energy fluxes have been conducted here since 1996 (Hollinger et al., 2004).

The undisturbed stand (mean stand age ≈ 110 y, maximum stand age ≈ 215 y; basal area $48 \pm 17\ m^2\ ha^{-1}$, mean ± 1 s.d., based on 48 FIA-style inventory plots) at the "Main tower" is atypical of contemporary Maine, particularly the surrounding landscape, where intensive forestry activities have taken place for over a century. In a nearby stand ("Block A"), a shelterwood harvest in 2007 removed approximately 40–50% of the basal area of canopy trees. The closed canopy in the Main stand contrasts sharply with the open canopy of Block A (Fig. 1).

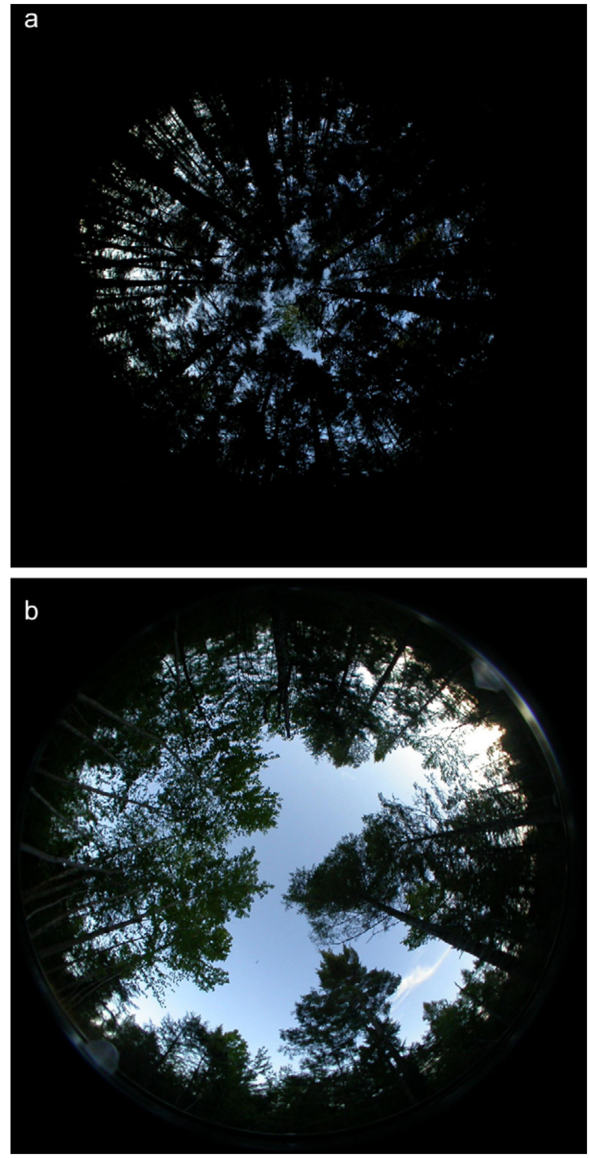

Fig. 1. Digital hemispherical photography images of the canopy in the Main (top) and Block A (bottom) stands at Howland Forest.

2.2. Leaf area index measurements

Optical instruments to measure LAI quantify gap fraction, essentially the probability of direct beam radiation penetrating through the canopy (e.g., Ryu et al., 2010). A 200 m transect, running in a N-S direction, was laid out in the Main stand; a similar transect, running E-W, was laid out in Block A. Measurement points were established at 10 m intervals and marked with flags. We walked each transect twice, on successive evenings, conducting simultaneous measurements each evening with both an LAI-2000 (Li-Cor Biosciences, Lincoln, NE) plant canopy analyzer, and a digital hemispherical photography (DHP) camera (Nikon Coolpix 4500) with a 180° fisheye lens (Nikon FC-E8) and monopod with a self-leveling mount (Hemiview SLM4, Delta-T Devices, Cambridge UK). All measurements were made at breast height (1.3 m above ground level). Measurements were conducted only when the sun was less than 15° above the horizon, based on standard astronomical tables. It took roughly 30 min to conduct a set of measurements along a single transect.

We used a pair of LAI-2000 wands. After cross-calibration and clock synchronization, following the manufacturer's instructions, the reference wand was mounted above the canopy on the 25 m high walk-up tower used for eddy covariance flux measurements. LAI-2000 data were processed using Li-Cor's FV2000 software program (http://envsupport.licor.com/docs/FV2000Manual.pdf).

For DHP images, we used a fixed exposure for each transect, rather than autoexpose each image. The importance of a consistent exposure has been emphasized by Leblanc (2005). We spot metered off the sky at zenith, then intentionally over-exposed the subsequent images by 2 full stops. When done in this way, there is strong contrast between foliage (dark) and sky (light), and at least in principle the threshold for separating foliage from sky should be the same in all images. Imagery was processed using the DHP software program (Leblanc, 2005).

Following Chen et al. (2006), leaf area index, L, is calculated as:

$$L = \frac{(1-\alpha) L_e \gamma_E}{\Omega_E} \qquad (1)$$

where α is the woody-to-total leaf area ratio, L_e is the effective (i.e., measured; technically speaking, what we are actually measuring is PAI, or plant area index, since branches and stems, as well as foliage, are included in our measurements) LAI, γ_E is the needle-to-shoot area ratio, and Ω_E is the beyond-shoot clumping index. We used literature values for black spruce, from Chen et al. (2006), for α (0.15) and γ (1.6), as both parameters are labor-intensive to measure. For conifers, typical values are 0.10–0.20 for α 1.4–1.9 for γ_E. For non-flat leaves, the measure of LAI thus obtained equals one-half of the total intercepting area per unit ground surface area, as proposed by Chen and Black (1992).

LAI-2000 and DHP were used to determine L_e for each measurement point. We expected Ω_E to differ between Main and Block A, because the large canopy gaps resulting from the shelterwood should be manifest as substantial beyond-shoot clumping. By comparison, the closed canopy is much more uniform in the undisturbed forest around the Main tower. The theory and practice of measuring Ω_E is beyond the scope of this brief note (see, for example, Leblanc, 2005; Chen et al., 2006), but we note that it can be estimated either with the TRAC (Tracing Radiation and Architecture of Canopies; Leblanc et al., 2005) instrument, or by processing the DHP images into "TRAC-like transects" which are then analyzed by software for the TRAC instrument (Leblanc, 2005). Using the latter approach, we determined values of 0.98 (Main) and 0.88 (Block A) for Ω_E. Ryu et al. (2010) have argued that the FV2000 software, because it calculates Le as the mean of the logarithms of the individual gap fraction measurements, rather than the logarithm of the mean gap fraction, already incorporates an apparent clumping factor. Based on their analysis, Ryu et al. (2010) estimated apparent clumping values of 0.96 and 0.89 for Main and Block A, respectively. Ryu et al. (2010) propose that if the FV2000 approach is used, then the Ω_E term should be dropped from Eq. [1] to avoid double-counting of clumping effects.

Uncertainties in Ω_E, α and γ are not explicitly considered here. Chen (1996) reported uncertainties of roughly 10% for each of these terms.

3. Results

3.1. Spatial patterns and sampling uncertainty

For the Main transect, the LAI-2000 measured a somewhat higher mean L_e than DHP (4.08 vs. 3.61, based on the arithmetic mean of the point measurements, cf. Ryu et al., 2010), but for Block A, both instruments were similar (1.85 vs. 1.82, respectively). Spatial patterns along the two transects were comparable for both instruments, as illustrated in Fig. 2. On the first day of measurements, the spatial correlation of LAI-2000 L_e vs. DHP L_e was $r = 0.92$ for the Main transect and $r = 0.97$ for Block A (averaged across both days of measurements, the corresponding values are both $r = 0.98$). This increases our confidence in the ability of each instrument to

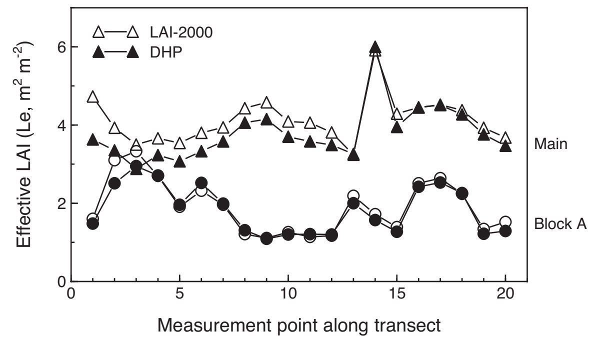

Fig. 2. Spatial patterns of variation in leaf area index ("effective" LAI Le, in $m^2\ m^{-2}$) along two transects ("Main", triangles, and "Block A", circles) at the Howland Forest, using two different measurement techniques, the LAI-2000 plant canopy analyzer (open symbols) and digital hemispherical photography (DHP, filled symbols). Data are shown for the first day of measurements.

detect differences in canopy structure. The observed standard deviation of L_e was 0.60 for the Main transect and 0.70 for Block A, indicating a sampling uncertainty (one standard error) for each transect of roughly 0.15 given $n = 20$ measurement points.

For comparison, periodic LAI-2000 measurements (mid-summer in 1998, 2001, 2003, and 2006) at a wider network of 24 plots around the main tower indicated an arithmetic mean L_e of 3.9, with a mean spatial variability (one standard deviation, average for each of the four years) of 0.4, and a sampling uncertainty (one standard error) of 0.1. Thus, mean L_e along the Main transect is similar to that for the forest as a whole surrounding the Main tower, but there is somewhat more spatial variability along the transect compared to the wider network of plots.

3.2. Random uncertainty and bias from repeat measurements

The LAI-2000 measurements were more repeatable, with a mean absolute difference (between L_e measured on the first pass and L_e measured on the second pass) of 0.14, compared with 0.26 for DHP. Including both transects, the linear correlation between measurements on the first pass and those on the second pass was correspondingly higher for LAI 2000 ($r = 0.994$) than DHP ($r = 0.977$), but this statistic tends to mask the appreciably better performance (clearly visible as reduced scatter in Fig. 3) of the LAI-2000 compared to DHP.

In previous work (Hollinger and Richardson, 2005), we showed how paired flux measurements (e.g., simultaneous measurements

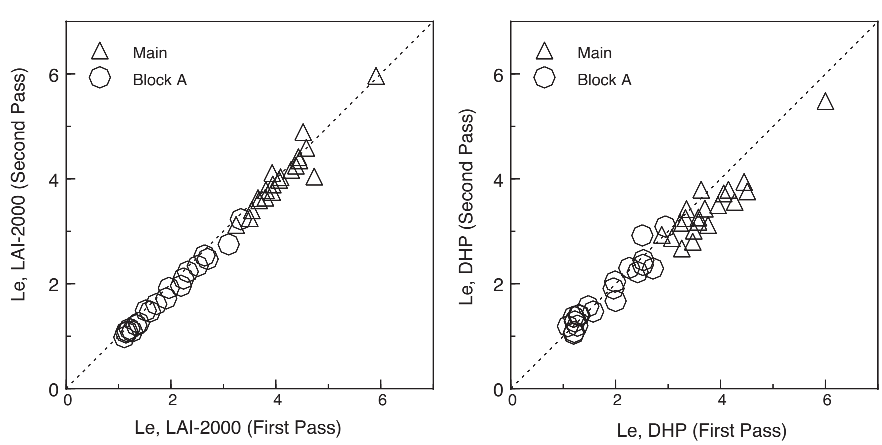

Fig. 3. Agreement between repeat leaf area index measurements ("effective" LAI, Le, in $m^2\ m^{-23}$) along two transects ("Main" and "Block A") at the Howland Forest, using two different measurement techniques, the LAI-2000 plant canopy analyzer (left) and digital hemispherical photography (DHP, right). Dotted diagonal line is 1:1.

from two towers with non-overlapping measurement footprints) could be used to estimate the statistics of the random flux measurement error; basically, if $x_{i,1}$ and $x_{i,2}$ are the paired measurements at time i, and ε is the random measurement error associated with each x, then $\sigma(\varepsilon) = \sigma(x_{i,1} - x_{i,2})/\sqrt{2}$ where the standard deviation is computed across all pairs $x_{i,1}$ and $x_{i,2}$. In an analogous manner, we used the repeat measurements along each transect (subscript i now denoting plot number, and measurements 1 and 2 referring to the first and second pass along each transect) as the basis for quantifying random LAI measurement uncertainty. With this method, we estimate the standard deviation of the random measurement uncertainty, $\sigma(\varepsilon)$, for LAI-2000 as 0.20 and 0.07 for Main and Block A, respectively (~5% in both cases). For DHP, the corresponding values were 0.27 and 0.19 (~10%). We could not reject the hypothesis that the relative measurement errors are normally distributed.

The mean difference, $\mu(x_{i,1} - x_{i,2})$, gives us an order-of-magnitude estimate of potential bias due to daily calibration errors or differences in measured L_e that result from differences in sky conditions (e.g. changes in cloudiness and, consequently, scattering). For both instruments, L_e measured on the first pass was somewhat higher than on the second pass, as can be seen from the offset against the 1-1 line in Fig. 3. For the LAI-2000, the mean difference was similar in magnitude between Main (arithmetic mean L_e = 4.12 vs. 4.04, or 2%) and Block A (L_e = 1.92 vs. 1.78, or ~10%), whereas for DHP the difference between measurement dates was much larger in Main (L_e = 3.78 vs. 3.43, or 10%) than Block A (L_e = 1.83 vs. 1.81, or 1%). Thus, for both instruments, calibration errors may easily lead to systematic biases of 10% or more.

3.3. Other sources of uncertainty

The ratio of L_e measured with the LAI-2000 to L_e measured by DHP decreased by 10–20% over the course of walking each transect. This pattern was not caused by differential instrument sensitivities to a canopy structural gradient along the transect, as the pattern was observed both on the first pass and the second pass, when the transect was walked in reverse direction. That is, on the first day of measurements, the ratio declined from ~1.2 to 1.0 over the course of walking out along the transect, from measurement point 1 to 20. On the second day of measurements, the ratio declined from ~1.2 to 1.1 as we walked in along the transect, from point 20 to 1. Thus, the offset between the two instruments varied along the length of the transect, in a predictable, time-varying way. On the first day, the lowest offset was for plots 11–20, whereas on the second day, for plots 1–10. We attribute this pattern to changing illumination conditions (sky brightness) over the time it took to walk each transect, and the fact that the DHP exposure was kept constant. The dense canopy along the Main transect made more frequent exposure adjustment essentially impossible. Our experience (from an earlier measurement campaign), substantiated by reports of Chen et al. (2006) and others, was that automatic determination of the exposure for each DHP image would result in measurements of L_e that were not repeatable. By comparison, the express purpose of the LAI-2000 reference wand is to allow correction for changing conditions.

For both LAI-2000 and DHP, the raw data may be processed in different ways. The LAI-2000 calculates L_e on the basis of transmittance through the canopy at five different zenith angles. Chen et al. (2006) note that multiple scattering by leaves is a potential source of underestimation of LAI at large zenith angles. Chen et al. (2006) suggest comparing L_e for rings 1–5 with L_e for rings 1–3 (i.e., omitting rings 4 and 5, corresponding to zenith angles 45–60° and 60–75°, respectively). We found that L_e calculated for rings 1–3 tended to be about 20% higher than L_e calculated for all rings (4.93 vs. 4.12 for Main, 2.32 vs. 1.92 for Block A), and therefore acknowledge this as a potential bias in our estimates of L_e. However, our analysis indicated that repeatability was better when all rings were used.

Similarly, DHP images can be analyzed using either the whole image (0–81°; following Miller's integration, see Leblanc, 2005), or just certain zenith angle rings. Our results indicated better agreement between the first and second passes along each transect when the whole image was used, compared to individual rings. As was observed with the LAI-2000, higher zenith angle rings (i.e., 58.5°) generally gave 10–20% lower L_e estimates than lower zenith angle rings (i.e., 40.5°) for DHP, although on the second pass along the Main transect, exceptions to this were observed.

4. Discussion

Several previous papers have reported estimates of LAI measurement uncertainty, but the methods on which these estimates are based have not always been clear. Welles and Norman (1991) reported that repeated measurements within several minutes differed by <2%, whereas repeated measurements on the same day but hours apart differed by up to 10%. Ultimately, they concluded that LAI error was less than 15%. Chen (1996) and Chen et al. (2006) reported that instrument errors together resulted in uncertainties of less than 5% for L_e, but did not explain how this value was determined. Hyer and Goetz (2004) noted LAI uncertainties due to differences associated with specific models of instrument, data processing, and varying sky conditions, but did not quantify the standard deviation of the uncertainty for each of these terms. Previous modeling papers have assigned uncertainty to measured LAI without explaining the derivation of these uncertainty estimates (10%: Williams et al., 2005; Fox et al., 2009; 10–30%: Raupach et al., 2005).

Our objective here has been to develop, in a transparent manner, uncertainty estimates for leaf area index (LAI) measurements made using two commonly used optical instrument-based approaches, the LAI-2000 plant canopy analyzer and digital hemispherical photography. These uncertainties are needed so that LAI data can be incorporated into data–model fusion analyses in a statistically rigorous manner (e.g., Richardson et al., 2010). An important aspect of this is using the uncertainties to judge when data and model are consistent or inconsistent—i.e., if the data–model mismatch is significantly larger than the inherent data uncertainties, then this indicates the presence of substantial model structural errors, which should be addressed by changes to the model itself.

Sampling uncertainty arises from conducting a finite number of measurements rather than a complete census of the entire ecosystem. We estimate the L_e sampling uncertainty (one standard error) to be about 0.15 for each transect, given n = 20 measurement points. More extensive sampling in each stand would be one way to reduce the sampling uncertainty.

We have proposed that repeat measurements of a transect or set of plots, when made over a sufficiently short time interval that changes in the state of the canopy are likely to be negligible, can be used to quantify additional uncertainties in leaf are index measurements. Rather than directly compare the measurements from two different instruments (e.g., Figs. 1 and 2 in Chen et al., 2006), we instead compared two sets of measurements from the same instrument (our Fig. 3), and inferred the statistics of the random measurement error from the difference in paired measurements. For an individual measurement, random errors (1σ) were roughly twice as large for digital hemispherical photography (~10%) as for the LAI-2000 plant canopy analyzer (~5%). The impact of these random errors would be reduced by averaging across multiple plots or measurement points. (To the extent that random errors are partially attributable to operator error—including, but not limited to factors such as the sensor head not being perfectly level, or not being precisely located directly over the plot center—random errors can also be reduced by an attentive and skilled instrument operator.)

Another source of uncertainty is systematic bias due to instrument calibration. With only two measurements of each transect, we do not have a lot of data with which to estimate the magnitude of this potential error, but for both instruments, systematic errors of 10% or more are clearly possible. This error is systematic because it affects all measurements made with a particular calibration, and thus the impact is not reduced by averaging across multiple plots or measurement points. However, the bias has a random component because the calibration error is inherently stochastic. For DHP, changing light levels over the course of measurements is an additional source of time-varying bias, which may be difficult to quantify. Correction for this should be possible, however, by measuring a specific reference plot immediately after, and then again immediately before, changing the camera exposure setting. With careful cross-calibration of the LAI-2000 wands, or exposure setting for DHP, these calibration errors can probably be largely reduced if not eliminated.

Data processing (e.g., selection of different zenith angle rings) decisions may add additional uncertainty. For example, multiple scattering by leaves at high zenith angles may result in systematic under-estimation of L_e if data from all zenith angles are used; omitting rings 4 and 5 from the LAI-2000 calculations resulted in a 20% increase in L_e. Corrections for multiple scattering are discussed by Chen et al. (2006), but require assumptions (e.g., spherical leaf angle distribution) which may not be valid for all vegetation types. Evaluation of optical measurements against different types of leaf area index (e.g., from litterfall traps or destructive sampling, e.g., Gower et al., 1999; Breda, 2003) data may be useful for resolving these issues, but the uncertainties of the other data must also be kept in perspective as well—a true reference value for LAI is difficult, if not impossible, to obtain (see, for example, the analysis of statistical uncertainty in allometric estimates of LAI provided by Woods et al., 1991).

Some of the systematic biases we have not attempted to quantify, such as those associated with the specific values chosen for parameters Ω_E, α and γ in Eq. (1), are no doubt important as well, particularly if data from different sites (where different assumptions about these parameters may have been made) are being analyzed together. Furthermore, the new method for averaging individual *L*e measurements, as proposed by Ryu et al. (2010), should be adopted to adequately account for clumping.

Although combining random and systematic error components into a single quantity is appealing, it is also a challenge, and there is no universally agreed-upon method for doing so (Petersen et al., 2001). Systematic errors must be corrected before the data are introduced into the model–data fusion scheme, or the bias may be propagated forward (Williams et al., 2009). Because LAI is a critical parameter for scaling traits and processes from leaf-level to ecosystem-level, reconciliation of these biases is essential.

4.1. Summary and conclusion

Rather than advocate the use of one instrument over another (i.e., LAI-2000 vs. DHP), our objective here has been to present an approach to quantifying random and systematic errors in projected leaf area index measurements. These data are needed to incorporate LAI measurements into a multiple-constraints data model fusion analysis. Mis-representation or under-estimation of data uncertainties may lead to inaccurate modeling results being assigned high confidence. As an example, uncertainty estimates affect how well the model predictions must "hit" the measured values. If LAI uncertainties are over-estimated, then the amount of information contributed by these data to the analysis will be reduced, because a poor data–model mismatch may still yield a statistically "acceptable" fit. By comparison, if LAI uncertainties are under-estimated, the model may be "pulled" towards tracking poor-quality leaf area measurements in which we are over-confident, at the expense of less accurate representation of other model components.

This kind of error analysis is also needed to inform efforts at reducing measurement uncertainties. Given our sample size, random uncertainties are substantially smaller than the spatial variation, as well as possible biases resulting from processing decisions (i.e., Which zenith rings should be used to estimate L_e?), and potential systematic calibration errors. Careful attention to calibration, and the designation of individual measurement points for reference measurements, should help to keep calibration errors to an acceptable level.

Which of these errors are most important will likely vary depending on the nature of the analyses being conducted. Some systematic errors may not be relevant if, for example, monthly measurements from a set of plots at a single site are being used to inform modeling of seasonality or phenological processes. On the other hand, sampling uncertainty and choice of clumping parameter values may be the dominant sources of uncertainty if data from different sites are being incorporated in a regional carbon budget analysis. We note also that the nature of these uncertainties may vary from site to site, depending on site characteristics, sampling protocols, and so forth. Thus, we have described here a framework for quantifying different sources of error in LAI measurement, but have intentionally stopped short of providing a universally applicable estimate of "the uncertainty", because the relevant uncertainties are context-dependent.

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